Predicting consumers' trial/adoption of new technology: Revisiting the behavioral expectations - behavioral intentions debate

Abstract

Behavioral intentions (BI) is considered the key to understanding and predicting the trial/adoption of new technology. When choices of new technology adoption increases (and time compresses), it becomes correspondingly more difficult to predict consumers' trial/adoption. Due to its greater temporal stability and potentially superior predictive ability, this article encourages researchers to consider behavioral expectations (BE) ahead of BI. However, this ultimately depends on the antecedents germane to the particular new technology adoption process under examination. Thus, researchers are encouraged to consider the key determinants of BE: experience, perceived behavioral control, facilitating conditions, self-efficacy, attitudes, subjective norms, and availability of information.

Keywords: Behavioral expectation, Behavioral intention, Technology adoption, Temporal stability, Trying

Introduction

The marketing discourse on consumers' adoption of new technology draws primarily on conceptual models developed in psychology and information systems. The most cited models included the theory of reasoned action (TRA; Ajzen and Fishbein 1974, 1980) and the theory of planned behavior (TPB; Ajzen 1985, 1991), which together provided the conceptual basis for the technology acceptance model (TAM) in information systems research (Davis 1986). What these three well-regarded models have in common is their use of behavioral intentions (BI) as the principle predictor of behavior. In extant marketing literature, researchers similarly employed BI to predict behavior in different settings, including in the adoption of new technology (e.g., Lu et al. 2003).

Despite this widespread use of BI to predict consumers' adoption of new technology, it is by no means an infallible measure. Consequently, the identification of BI's boundary conditions remains a critical research gap (Bagozzi 2007). In models that incorporated BI as a sole immediate predictor of technology adoption, the underlying acceptance (or rejection) of new technology follows a specific sequence: intention to adopt → adoption and/or use → repeat purchase/patronage. According to Bagozzi et al. (1992), the TAM presumed that when a person forms BI judgments about accepting (or rejecting) new technology, s/he anticipates no impediments between BI formation and actual behavior, such as ability limitations, time constraints, environmental contingencies, or unconscious habits. This condition appeared to apply to the adoption of new technology items that are not problematic—in other words, in situations in which people believe that they have a high degree of control over their behavior (Bagozzi et al. 1992), such as deciding to adopt a new version of previously learned software. Moreover, even if consumers encounter problematic conditions, they may consider these issues foreseeable impediments that might challenge behavioral performance. Faced with an inconsistency between BI and actual behavior, Bagozzi and Warshaw (1990) suggested that the situation illustrates the pursuit of goals rather than reasoned behavior. These authors thus contended that BI has a limited ability to account for the impediments or uncertainty that challenge behavioral performance. Thus, researchers should find alternatives to BI as an immediate predictor of behavior, especially if the adoption of new technology is a goal.

Venkatesh et al. (2006) also highlighted some limitations of BI, most notably its modest ability to predict behaviors that are not under volitional control or that are subject to impediments. In searching for a better predictor of new technology adoption in an organizational setting (when the behaviors are often subject to impediments), these authors turned to research by Warshaw and Davis (1984) who suggested behavioral expectation (BE) rather than BI. In particular, Warshaw and Davis (1984) argued that BE can better explain the act of pursuing goals than BI can. For purely volitional behavior, both BE and BI are predictive (r_{BE} = .441, r_{BI} = .476), whereas for behavior that entails pursuit of a goal, BE is more predictive than BI (r_{BE} = .307, r_{BI} = .091). People who formed BE judgments can foresee impediments to behavioral performance, which initiated the act of trying (or not trying) to overcome impediments. Meanwhile, when people formed BI judgments, they ignored impediments to their behavioral performance; thus, they do not initiated any acts associated with trying. In turn, when the adoption of new technology appears as a goal, BE should be a better predictor than BI.

To address some of the aforementioned uncertainty, in this paper we compare different conceptualizations of BI and BE when the act of trying a new technology appears as a goal rather than a reasoned behavior. Marketing researchers need to explain the act of trying to adopt, in addition to the act of adopting, a new technology. In turn, we suggest that marketers should adopt BE as a more robust immediate predictor of behavior than BI when the consequences are goals rather than reasoned behaviors. In addition, we expect temporal stability to moderate the relationships between BI or BE and behavior. Whereas BE is likely to remain more stable over time for goals than for reasoned behaviors, BI should be more stable for reasoned behaviors than for goals. Finally, we offer recommendations about seven key antecedents to the formation of BE judgments: experience, perceived behavioral control, facilitating conditions, self-efficacy, attitudes, subjective norms, and availability of information. These important factors determine the act of trying and the act of using new technology in consumer settings.

We determine BE with factors that represent consumers' act of trying a new technology – to overcome impediments to behavioral performance. Furthermore, we conceptualize BI using factors that initiate consumers' act of using new technology, without worrying about the uncertain consequences before or during usage. Ultimately, we offer a new conceptual framework for researchers and practitioners. The different conceptualizations of BI and BE, as predictors of goals versus reasoned behaviors, offer the promise of improving the manner in which researchers in this domain predict consumer behavior.

This conceptual framework shed a light in understanding how BE is a better predictor of new technology adoption compared to BI. This review of consumer research will be useful for various contexts, particularly the retail context. According to Inman and Nikolova (2017), retailers are faced with an increasing array of potential technologies although retail technology capabilities are currently high. These authors noted that continual innovation and new technology (e.g., iBeacons, mobilePOS, Near Field Communications and Internet of Things) are critical in creating a sustainable competitive advantage. We believe that our paper will be beneficial in assisting researchers and practitioners in comprehending how consumers adopt the new retail technologies.

Behavioral expectations

Warshaw and Davis (1984) contended that BE is a more robust immediate predictor of goals than BI, whereas Ajzen and Fishbein (1974, 1980) had previously proposed TRA as a model to predict behavior by incorporating BI as an immediate predictor of behavior. When formulating the TRA, Ajzen (1985) offered two different conceptualizations of immediate predictors: BI and another construct that precedes BI that he labeled BE, claiming that "people will *expect* to perform a behavior if they *intend* to try it…" (Ajzen, p. 33) such that the degree of probability of performing a targeted behavior determines the level of control over it. That is, BE predicts an attempt to perform a targeted behavior, whereas BI predicts the likelihood of actually performing a targeted behavior. However, in subsequent work this author focused more on BI as a sole immediate predictor of behavior. Thus the TRA inherited the limitations of BI—in particular its limited ability to account for foreseeable impediments to behavioral performance (Warshaw and Davis 1985b).

Bound by this specific limitation, the TRA presumes that all behaviors are reasoned, and there is no impediment between BI and behavior (Bagozzi and Warshaw 1990). In contrast, Warshaw and Davis (1984) highlighted several impediments that might challenge behavioral performance, such as ability limitations, resource limitations, and unconscious habits. Behaviors that are subject to such impediments (i.e., goals) need a more robust predictor than BI, because BI cannot capture them (Warshaw and Davis 1984). Although Ajzen (1985) appears to overlook BE, we argue that it actually may be a better predictor of consumers' act of trying new technology.

Even as they proposed BE as a better predictor of goals than BI, Warshaw and Davis (1985a) reformulated the conceptualizations of these variables, observing that researchers have used them interchangeably. In particular, they worried that some BI measurement items actually measured BE in prior studies (Ajzen and Fishbein 1974, 1980). Thus, they worked to differentiate items that measure BI, such as "do you intend to" or "do you plan to," from items that measure BE, such as "do you expect to" or "are you going to." According to Warshaw and Davis (1985b, p. 218), BI measurement items captured "the degree to which a person has formulated conscious plans to perform specified future behavior," whereas BE measurement items captured "the individual's estimation of the likelihood that he or she actually will perform some specified future behavior." For example, a young scholar might answer affirmatively when asked whether s/he *intends* to publish in a top-tier journal, but the answer likely differs if the question is whether s/he *expects* to.

Finally, no prior studies have examined explicitly whether BE is a better predictor of goals than BI. For example, research indicated that BE can overcome BI's limitation as an immediate predictor of behavior, without explicitly distinguishing between goals and reasoned behaviors in various contexts, such as health-related behaviors (Richard et al. 1996), academic performance (Gordon 1989, 1990), exercise (Burgess et al. 2010; Rhodes and Matheson 2005), and new technology adoption (Venkatesh et al. 2006, 2008). However, these studies reported that BE is a better predictor than BI, despite the proposition that behaviors combine goals and reasoned behaviors.

There are various explanations for why BE might offer better predictive ability than BI. First, BE takes into account foreseeable events that may challenge behavioral performance, whereas BI's ability to address them is limited (Warshaw and Davis 1985b). Second, BE is better able to capture uncertainty than BI, because respondents who form BE judgments are more aware of factors that may decrease or increase the probability of performing the targeted behavior, compared with those who form BI judgments (Venkatesh et al. 2008). In the context of pro-environmental behavior, for example, Mahardika et al. (2011) contended that BE reflects a person's judgments about whether a targeted behavior is feasible or not, whereas BI reflects the desirability of the targeted behavior. The authors also observed that people make better estimations of their actual behavior when they responded to BE questions rather than BI questions. Third, the role of BE differs from the role of perceived behavioral control (PBC) in the theory of planned behavior. Konerding (2001) argued that unlike PBC, which captures only factors under respondents' control, BE captures factors both within and beyond their control. This argument receives support from empirical studies that investigate the effects of PBC on the predictive ability of BE and BI (e.g., Rhodes and Matheson 2005; Venkatesh et al. 2006).

Behavioral expectation versus behavioral intention

Experts considered BI as the most widely adopted construct for understanding, examining, and predicting the adoption of new technology in various consumer settings

(Okazaki 2005). A literature search (Dec 2011) using "behavioral intention" and "intention" as keywords illustrates the extensive use of BI in marketing research. Among marketing journals included in the Business Source Premier database from 1950 to 2011 (see Table 1), 6,526 articles mentioned "intention" in the body text, 1,420 texts mentioned one of the keywords in the abstracts, and 376 used one of the keywords in their titles. A narrower search, focused on the consumer setting, revealed that 5,717 articles mentioned "intention" in the body text, 1,143 included the keyword in their abstracts, and 299 used one of these keywords in their titles. A third search focused on organizational settings revealed that 2,777 articles mentioned "intention" in their body text, 308 used it in their abstracts, and 66 used it in their titles. In contrast, BE has received scant interest from marketing researchers; a literature search using "behavioral expectation" as a keyword (though not "expectation," because it has a distinct, well-established definition in marketing literature) but excluding scales indicated only 10 articles that mentioned "behavioral expectation" in the body text, and not a single study mentioned it in the abstract or title. These 10 articles all fell within the consumer setting; with one of them also pertained to an organizational setting. As Table 1 demonstrate, extant marketing literature appears to have largely overlooked BE.

Perhaps the main reason for this lack of consideration is that BE is equally not well recognized in other fields, including psychology, where the concept first surfaced. A count of the number of studies that cited the primary resources on BE (Warshaw and Davis 1984, 1985a, 1985b) reconfirmed this scant attention (see Table 2). According to the Google Scholar database, the 26 citations of Warshaw and Davis's (1984) introduction of BE included 10 psychology texts, but no marketing articles. The 40 citations of Warshaw and Davis's (1985a) next text represent all fields, though the majority was in psychology (8) and social psychology (6), as well as information systems (5), and health (4). Finally, we found 243 citations of the third (and main) article by Warshaw and Davis (1985b), including 52 in cognitive psychology, 31 in social psychology, and 26 in health fields. Scholars across disciplines have not given BE adequate attention, and marketing scholars are perhaps the most significant group to overlook it as a better immediate predictor of behavior. The

Table 1 Summary of BI and BE in marketing literature

Area of Research	Behavioral Intention			Behavioral Expectation		
	Mentioned in Body Text	Quoted in Abstract	Used in Title	Mentioned in Body Text	Quoted in Abstract	Used in Title
All	6,526	1,420	376	10	none	none
Consumer	5,717	1,143	299	10	none	none
Organization	2,777	308	66	2	none	none

Source: Business Source Premier, 1950–2011.

Table 2 Summary of BE in literature

Area of Research	Primary Studies		
	Warshaw and Davis (1985b)	Warshaw and Davis (1985a)	Warshaw and Davis (1984)
All Fields	243	40	26
Cognitive psychology	52	8	10
Social psychology	31	6	4
Information systems	9	5	5
Health	26	4	3
Marketing	11	1	0
Economics	2	0	0

*Source: Google Scholar, 1950–2011

question that arises is: Why do scholars overlook BE? To answer this particular question, we considered several possible explanations in the next section.

Why do scholars overlook BE?

We traced the first explanation for why scholars overlook BE back to the development of the TPB (Ajzen 1985), which suggested that BE can predict the attempt or intention (BI) to perform a targeted behavior. However, according to Morojele and Stephenson (1994), Ajzen abandoned this conceptualization of BE (e.g., Ajzen 1988, 1989, 1991). Schifter and Ajzen (1985) indicated that the underlying process of predicting actual behavior is similar to the underlying process of predicting an attempt to perform (Morojele and Stephenson 1994). We might speculate then that Ajzen chose to incorporate BI, and not BE, into the model to establish a sole immediate predictor of behavior. Subsequently, other studies that employed TPB and its extensions accordingly have excluded BE (Davis 1986).

The explanation of why researchers overlook BE also might be related to conceptual understanding of this construct. The findings from various studies showed that BE demands a different conceptualization than BI (e.g., Gordon 1990; Pomery et al. 2009; Venkatesh et al. 2006; Warshaw and Davis 1984, 1985a, 1985b), because intentions cannot address the basic question of "whether behavioral expectation qualifies in causal models of behavior" (Sheeran 2002, p. 12). Yet researchers seemingly accepted constructs in established causal models as sound if graphical diagrams or mathematical equations support their roles (Sutton 1998). In Konerding's (2001) initial attempt to address the issue, using statistical equations to differentiate the formation of BE and BI judgments, the results confirmed that BE has a causal effect on actual behavior, which lays the groundwork for further study.

Another explanation is potential redundancy between PBC and BE. Sutton (1998) reported that in various studies that have applied TRA and TPB, the effect size of BI in predicting non-volitional behavior increases when PBC is incorporated. Warshaw and Davis (1985b) argued that BE can overcome BI's limited ability to predict behavior though without acknowledging that this effect pertains only to behavior that is not under volitional control.

Fishbein and Stasson (1990) also asserted that BE's predictive ability is not significantly better than BI's for behavior that is not under volitional control. Thus, BE may be redundant with PBC. However, Venkatesh et al. (2006) contended that PBC has limited ability to overcome the tendency of BI to change over time, because it cannot capture factors that are beyond a person's control either, such as uncertainty. BE is more stable over time because it can better account for factors beyond a person's control (Venkatesh et al. 2006; Warshaw and Davis 1984). Thus, BE and PBC demand different conceptualizations, and each plays a distinctive role in dealing with the limitations of BI.

A final explanation is related to the predictive performance of BE. Although BE offers greater predictive ability than BI, the difference is trivial and inconsistent across different types of behaviors. Sheppard et al.'s (1988) meta-analysis revealed that the average correlation for BE is 0.57 and that for BI is 0.49, which they considered insufficiently reliable to prove that BE's predictive ability is significantly better than BI's. Similarly, Sheeran and Orbell (1998) found insignificant differences in the average correlation between the estimate and intention measures. However, Warshaw and Davis (1985b, 1992) contended that researchers should avoid using items from both constructs interchangeably when comparing the average correlations of BE and BI. Thus, in the following section, we meta-analyze 10 articles that compared BE with BI, using specific terminology and items (Warshaw and Davis 1985b).

Why should scholars recognize behavioral expectations?

The act of trying. Researchers seemingly have overlooked BE because some reports suggested that it addresses BI limitations only trivially. Yet the efficacy of BE should be a better predictor of behavior than BI, and thus marketing researchers need to distinguish observed behaviors in accordance with Bagozzi and Warshaw's (1990) guidelines. That is, not all behaviors are reasoned behaviors; therefore, some behaviors must be associated with the pursuit of goals. A behavior is goal related when people who will exhibit it foresee impediments. Conversely, a behavior is reasoned when people do not expect or foresee any impediments to their performance. Bagozzi et al. (1992) proposed new technology adoption constitutes a goal pursuit goal when there are impediments, such as limited ability, that affect the likelihood people will adopt it. For example, deciding to upgrade to a new version of a statistical software program is a reasoned behavior, because people are unlikely to foresee impediments. In contrast, deciding to purchase a new statistical software program with which they are not familiar is a goal, because they foresee impediments (e.g., learning). When people have behavioral goals, they judge whether to try (or not try) to overcome the impediments.

The importance of BE becomes more obvious, especially to marketing researchers, if they realize its role in capturing consumers' acts of trying. Bagozzi and Warshaw (1990) explained that consumers initiate trying when the consumption is problematic and the anticipated action is a goal. Theoretical models that employed BI instead aim to predict the act of using, rather than the act of trying (Bagozzi et al. 1992). Behavioral intentions have limited ability to predict goals, because the formation of a person's BI judgments does not take into account uncertain consequences before or during the performance (Bagozzi and Warshaw 1990). Warshaw and Davis (1985a) further suggested that BE is a more robust predictor of trying than BI, because a person who forms BE judgments is aware of impediments that may stand in the way. Three factors associated behaviors with goals: (1) scarcity of supply, (2) scarcity of resources, and (3) a limited or unfeasible time period for performing the behavior (Bagozzi and Warshaw 1990). As we mentioned previously, BE reflects the feasibility of performing a behavior; it already considers these three factors. More important, BE should be an accurate representation of the likelihood of people trying (or not trying) to overcome the impediments that stand in their way. Thus, it is important to understand the conceptualization of BE as an immediate predictor of goals.

Predictive ability. In a meta-analytic review of studies that used BI as an immediate predictor of behavior, Sutton (1998) found that BI can explain 19% and 38% of the variance (i.e., correlation of .44–.62). Another meta-analysis by Sheeran (2002), using 10 meta-analytic studies, suggested that BI explains 28% of variance (correlation of .53). These studies concurred in the assessment that BI's predictive ability is weak; it explains less than 50% of the variance. However, these studies did not follow Warshaw and Davis's (1985b) recommendation to disentangle BE and BI items.

For our meta-analysis, we adopted this distinction and selected 10 studies of BE versus BI, using two criteria. First, each study disentangled the BE and BI items in accordance with Warshaw and Davis' (1985b) recommendation. Second, the studies measured actual behavior and correlated it with either BE or BI measurements. In Table 3 (panel a), we display the results of this meta-analysis and the correlations with behavior, whether goals or reasoned behaviors. Table 3, Panel b, contains the results when we limit the correlations to goals. In all selected studies, the predictive ability of BE exceeded that of BI.

The total sample size was 2,550 for BE and 2,532 for BI. The BE–behavior correlations ranged from .38 to .64, with an average of was .51; the BI–behavior correlations ranged from .20 to .52, with an average of .40. On average, BE explained 26% of the variance, whereas BI accounted for 16%. Cohen's (1992) power primer offers a useful basis for analyzing correlations and R-square values: A small effect size is $r_+ = .10$, a medium effect size requires $r_+ = .30$, and a large effect size indicates that $r_+ = .50$. Thus, the average BE–behavior correlation ($r = .51$) was large, whereas the average BI–behavior correlation ($r = .40$) was a medium effect size. A paired test of differences using the Fisher's Z transformations of the BE–behavior and BI–behavior correlations showed that the former were significantly greater than the latter across 10 studies ($t(9) = 4.95$, $p < .05$, one-tailed).

The results in Table 3 reveal that the predictive ability of BE and BI was equal for reasoned behavior (Panel c), but BE was significantly more predictive than BI for goals (Panel b). Three studies measured the predictive ability of BE/BI for both goals and reasoned behavior: Warshaw and Davis (1984), Warshaw and Davis (1985b), and Konerding (2001). We calculated them separately to determine the varying strengths of the correlations; all other studies measured goals only. The BE–goals correlations ranged from .34 to .64, with an average of .50 (large effect size). The BI–goals correlations ranged from .13 to .52, with an average of .38 (medium effect size). On average, BE explained 25% of the variance, whereas BI accounted for 14%. The paired test of differences using Fisher's Z transformations confirmed that the BE–goals correlations were significantly greater than the BI–goals correlations across 10 studies ($t(9) = 5.32$, $p < .05$, two-tailed).

For the BE–reasoned behaviors, the correlations ranged from .36 to .43, and the average correlation was .40 (medium effect size), whereas the BI–reasoned behaviors correlations ranged from .23 to .41, and the average correlation was .34 (medium effect size). Moreover, BE explained 16% of the variance for reasoned behavior, whereas BI explained 12%. This paired test of differences using Fisher's Z transformations shows that BE–reasoned behavior and BI–reasoned behavior correlations were not significantly different across three studies (t(2) = 0.76, $p < .05$, two-tailed).

Temporal stability. Although researchers have overlooked it, BE helps address the temporal stability of BI and its poor predictive ability (Sheeran 2002). According to Sheeran and Orbell (1998), researchers used BI widely because of its high propensity for change over time, though they also report that the predictive ability of BI diminishes as its time interval with actual behavior increases. Ajzen and Fishbein (1974) also noted that as the time between BI and the actual behavior increases, there is a greater propensity for BI to change, which lowers its predictive ability (see also Albarracin et al. 2001; Armitage and Conner 2001). That is, the predictive ability of BI depends on its temporal stability, which Sheeran and Abraham (2003, p. 206) defined as "the extent to which an immediate predictor of behavior (e.g., BI) persists over time regardless of whether it is challenged." A shorter interval between BI and behavior observations leads to a stronger BI–behavior correlation. Thus, to increase BI's predictive ability, Ajzen (1985, 1991) suggested measuring actual behavior immediately after measuring BI—an approach we consider impractical.

Moreover, the gap between BI and actual behavior constitutes a key issue for conceptual models that employ BI as a sole immediate predictor (Sutton 1998), in that respondents who indicate strong intentions to perform a targeted behavior do not necessarily do so. Sheeran (2002) identified possible sources of this gap: First, a person's BI judgments may change over time, so a longer the time interval between the measurement of BI and the behavior increases the chances of unforeseen events that might lead to changes in BI (Warshaw and Davis 1985b). Bagozzi (2007) thus suggested that a link between BI and action initiation is required, because BI changes over time to conform with anticipated or unanticipated interventions and obstacles. Second, BI may be provisional; studies that employ it as an immediate predictor of behavior rarely place their respondents

Table 3 Meta-analyzes

a. BE–behavior versus BI–behavior correlations

Study	BE–Behavior			BI–Behavior		
	n	R^2	***r***	***n***	R^2	***r***
Warshaw and Davis (1985a)	39	0.14	0.38	39	0.07	0.27
Warshaw and Davis (1985b)	113	0.27	0.52	84	0.21	0.46
Gordon (1989)	81	0.30	0.55	82	0.19	0.44
Courneya and McAuley (1993)	170	0.20	0.45	170	0.13	0.36
Konerding (2001)	107	0.13	0.36	107	0.04	0.2
Rhodes and Matheson (2005)	241	0.30	0.55	241	0.27	0.52
Venkatesh et al. (2006)	1,182	0.22	0.47	1,182	0.15	0.39
Venkatesh et al. (2008)	321	0.41	0.64	321	0.18	0.43
Pomery et al. (2009)	254	0.27	0.52	254	0.17	0.41
Mahardika et al. (2011)	42	0.38	0.62	52	0.26	0.51
Overall	**2,550**	**0.26**	**0.51**	**2,532**	**0.16**	**0.40**

b. BE–goal versus BI–goal correlations

Study	BE–Goals			BI–Goals		
	n	R^2	***r***	***n***	R^2	***r***
Warshaw and Davis (1985a)	39	0.12	0.34	39	0.02	0.13
Warshaw and Davis (1985b)	113	0.26	0.51	84	0.18	0.43
Gordon (1989)	81	0.30	0.55	82	0.19	0.44
Courneya and McAuley (1993)	170	0.20	0.45	170	0.13	0.36
Konerding (2001)	107	0.13	0.36	107	0.03	0.18
Rhodes and Matheson (2005)	241	0.30	0.55	241	0.27	0.52
Venkatesh et al. (2006)	1,182	0.22	0.47	1,182	0.15	0.39
Venkatesh et al. (2008)	321	0.41	0.64	321	0.18	0.43
Pomery et al. (2009)	254	0.27	0.52	254	0.17	0.41
Mahardika et al. (2011)	42	0.38	0.62	52	0.26	0.51
Overall	**2,550**	**0.25**	**0.50**	**2,532**	**0.14**	**0.38**

c. BE–reasoned behavior versus BI–reasoned behavior correlations

Study	BE–Reasoned Behavior			BI–Reasoned Behavior		
	n	R^2	***r***	***n***	R^2	***r***
Warshaw and Davis (1985a)	39	0.18	0.43	39	0.17	0.41
Warshaw and Davis (1985b)	113	0.16	0.40	84	0.14	0.38
Konerding (2001)	107	0.13	0.36	107	0.05	0.23
Overall	**259**	**0.16**	**0.40**	**230**	**0.12**	**0.34**

in a real decision-making scenario. Thus, BI judgments in the questionnaire are hypothetical or provisional.

For example, the stability of a person's BI judgments about adopting a pro-environmental lifestyle may be determined by various anticipated or unanticipated factors, such as commitment, that challenge the adoption of such lifestyle. Because BI grows less stable as the time interval between its formation and the pro-environmental action increases, along with the number of anticipated or unanticipated events, this limitation decreases BI's predictive ability over an extended prediction period. Thus Krosnick and Petty (1995) proposed two properties to determine the strength of an immediate predictor of behavior: impact and durability. Impact explains the predictive ability of BI, whereas durability explains its temporal stability and resistance over time. Because temporal stability determines the predictive ability of BI, it can serve as an initial indication of BI's predictive strength (e.g., Conner et al. 2000; Sheeran et al. 1999). Sheeran et al. (1999) reported that a stable BI strengthens the relationship with behavior, compared with an unstable BI. In addition, BI stability should moderate the relationship between past and future behavior. This notion has also been found evident in various area, including consumers' adoption of new technology (Mahardika, 2013; Maruping et.al., 2017).

Temporal stability of trying. Conner et al. (2000) also reported that the strength of the BI–behavior correlation is fully mediated by BI's temporal stability, which varies across situations, mainly because BI cannot effectively account for a person's sense of control over the performance of the behavior, especially when the behavior is a goal (Warshaw and Davis 1985a). To increase the temporal stability of BI, Sheeran (2002) suggested incorporating a construct that can capture this sense of control; the construct also should capture the stability of a person's trying over time. Among constructs that possess such capability is BE (Warshaw and Davis 1985a).

Since BE can account for a person's sense of control over trying to perform a targeted behavior (Konerding 2001), it should be more stable over time and thus have greater predictive capabilities than BI. Prior comparisons of BI and BE have focused on how well both constructs predict actual behavior (e.g., Pomery et al. 2009; Venkatesh et al. 2008; Warshaw and Davis 1984, 1985a, 1985b), not their temporal stability. However, two studies offered initial empirical support that BE has greater temporal stability than BI. Gordon (1989) observed that BE is a better predictor than BI when the interval prior to actual behavior increases. This finding signifies that BE is more stable over time and is reflects people's sense of control over performing a targeted behavior.

Venkatesh et al. (2006) compared the role of anticipation in moderating the relationships of BE and BI with actual behavior. A longer time interval (higher anticipation) strengthens the BE–behavior relationship but weakens the BI–behavior relationship. Thus, the effects of time are contradictive between BE and BI, likely due to BE's superior ability to capture foreseeable events that might challenge the performance of an actual behavior (Venkatesh et al. 2006). Despite observing the role of time for the prediction of behavior, neither Gordon (1989) nor Venkatesh et al. (2006) explored notions of temporal stability, though their studies provide a useful foundation for further examination of the topic.

Conner et al. (2000) reported that the strength of BI–behavior correlation is fully mediated by BI's temporal stability, which they posit varies across different situations because BI has only limited ability to account for a person's sense of control over goal-directed behavior (Warshaw and Davis 1985a; Sheeran 2002). When the behavior is a goal, a person who forms BE judgments foresees impediments and adjusts his or her assessment of probably success or failure accordingly, both before and during the performance of the behavior (Bagozzi and Warshaw 1990). His or her BE judgments regarding pursuing goals should be more stable over time than BI judgments would be. In turn, we propose:

> P_1: *Behavioral expectations are more stable predictor of goals compared to behavioral intentions.*
>
> P_2: *Temporal stability moderates the relationships between behavioral expectations and goals.*

Key Determinants of Behavioral Expectation

The predictive ability of BE encounters some boundary conditions. That is, BE may be a better immediate predictor of behavior than BI in some contexts (e.g., Courneya and McAuley 1994; Rhodes and Matheson 2005; Venkatesh et al. 2006, 2008), but this assertion may not hold in every context. Thus, we attempted to identify when and in what situations BE outperforms BI as an immediate predictor of new technology adoption in a consumer setting. Specifically, this article details some key factors that play an important role in the formation of consumers' BE judgments toward trying a new technology. Whereas researchers have overlooked this influence, we delineate the key determinants of BE and thereby extend the discussion of BE, as well as find the limits to its predictive ability.

We searched for relevant keywords, such as *behavioral expectation*, *self-prediction*, *self-prophecy*, and *self-estimation*, on the Google Scholar, Business Source Premier, and Proquest databases. The results revealed 15 articles that included 21 constructs as determinants of BE (see Table 4). Of these 21 constructs, 7 were relevant to the context of consumers' adoption of new technology: experience, perceived behavioral control, facilitating conditions, self-efficacy, attitudes, subjective norms, and availability of information. Whereas prior research has included experience, PBC, facilitating conditions, and availability of information as determinants of BE to predict technology adoption in organizational settings (e.g., Venkatesh et al. 2008), no studies have explored the role of self-efficacy, attitudes, or subjective norms. Nor have any investigations applied these constructs as potential determinants of the act of trying.

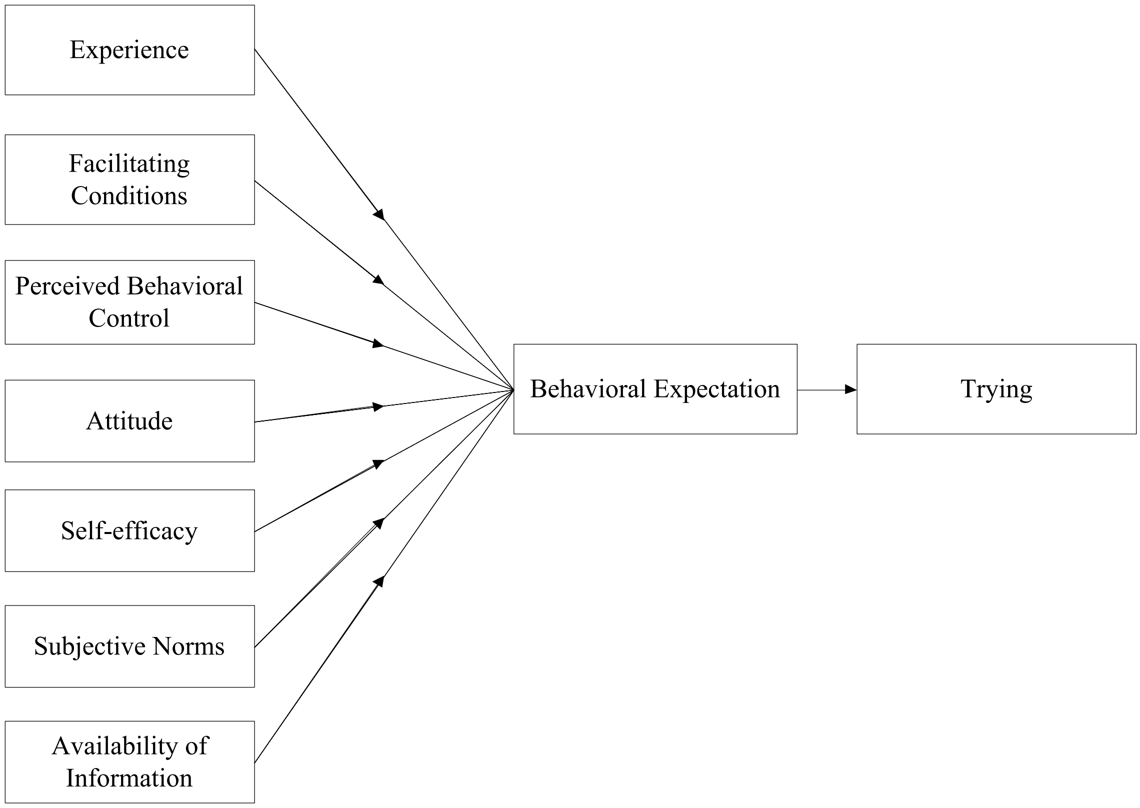
We propose a conceptual framework of the process underlying BE formation (see Figure 1). In addition to explaining the underlying process of BE judgments, we propose that the seven key determinants can specify the limits of BE's predictive ability, including why and in which situations BE provides a better predictor of new technology adoption than BI.

Venkatesh et al. (2006, 2008) provided initial findings about the roles of experience, PBC, availability of information, and facilitating conditions. Specifically, the effects of BE and BI on technology usage are fully moderated by experience (Venkatesh et al. 2006), such that more experience strengthens the relationship between BI and actual adoption/use but weakens the relationship between BE and actual adoption/use. Experience with a behavior provides information about that behavior, which is important in the formation of BI judgments but not as important for BE judgments. Venkatesh et al. (2008) also reported that

Table 4 Key determinants of BE for further research

Author	Determinants																				
	Behavioral Intention	Facilitating Conditions	Self-Understanding	Personal Base Rate	Circumstances	Personal Disposition	Attitudes	Behavioral Belief	Availablity Heuristic	Change in Intention	Peer support	Anticipation of Behaviour	Experience	Frequency of Behaviours	Non-cognitive Habit	Self-efficacy	Possible Environment Facilitators	Anticipated Affective Reaction	Perceived Behavioral Control	Subjective Norms	Availability of Information
Caroll 1978									X												
Warshaw and Davis 1984a			X																		
Warshaw and Davis 1984b										X					X	X	X				
Warshaw and Davis 1985	X																				
Osberg and Shrauger 1986	X			X	X	X															
Gordon 1989	X																				
Gordon 1990	X			X	X	X	X	X													
Courneya and McAuley 1994	X			X										X							
Richard et al. 1996							X											X	X	X	
Konerding 2001	X																		X		
Rhodes and Matheson 2004							X												X	X	
Venkatesh et al. 2006												X	X	X							
Venkatesh et al. 2008	X	X																			
Pomery et al. 2009													X								
Burgess et al. 2010	X			X																	
Conceptual model in this paper		**X**					**X**						**X**			**X**			**X**	**X**	**X**

Figure 1 Conceptual frameworks for trying new technology in the consumer setting



increasing experience or familiarity with the behavior provides information that people can use to estimate their control over that behavior. Moreover, experience significantly improves the sense of control in relation to BI judgments, but it adds only marginal effects in relation to a sense of control and BE judgments. Because experience with new technology likely reduces perceived uncertainty while increasing the sense of control, consumers with more experience with an innovation achieve greater awareness of the potential for anticipated or unanticipated impediments to actual adoption arise. In addition, the moderating effects of experience are greater in the BI–behavior relationship than in the BE–behavior relationship (Venkatesh et al. 2008).

Since people who form BI judgments rely on more abstract information, the effects of high versus low facilitating conditions should not differ much. In contrast, Venkatesh et al. (2008) reported that BE fully mediates the effect of facilitating conditions on the adoption of new technology, such that the high facilitating conditions lead to a stronger relationship between BE and adoption, whereas low facilitating conditions weaken it. Yet BI has limited ability to capture the effects of facilitating conditions. Thus, the different levels of facilitating conditions may not be fully reflected in the level of BI judgments.

Although there is substantial research into the role of BI as a mediator of the effects of attitudes, self-efficacy, and subjective norms on new technology adoption (e.g., Karahanna et al. 1999), we found no evidence or conceptualization on the role of BE. Venkatesh and Morris (2003) defined self-efficacy as the person's estimation of his or her ability to use technology to accomplish a particular job or task. Oliver and Shapiro (1993) found that people with high self-efficacy are more likely to succeed in technology-related tasks. Thus, a person with high self-efficacy should form higher BI judgments about adopting technology than a person with low self-efficacy. It would be worthwhile to explain how self-efficacy influences the formation of BE judgments—in particular whether the effects of self-efficacy increase a person's sense of control over adopting a new technology.

Finally, Ajzen and Fishbein (1974) theorized that BI is determined by two antecedents: attitude toward specific behavior, which reflects the degree of favorability of a person toward the targeted behavior, and the subjective norms that motivate a person to act in accordance with behaviors approved by others. Karahanna et al. (1999) contended that BI mediates the effects of attitude and subjective norms on technology, both before and after adoption. Specifically, the formation of BI judgments for potential adopters depends significantly on subjective norms, whereas their formation among users who already have adopted is more significantly influenced by attitude. It also would be beneficial to explain how the effects of attitude and subjective norms on technology adoption might be mediated by BE. In line with this review, we posit:

P_3: *The effects of experience on trying new technology are fully mediated by behavioral expectations.*

P_4: *The effects of perceived behavioral control on trying new technology are fully mediated by behavioral expectations.*

P_5: *The effects of facilitating conditions on trying new technology are fully mediated by behavioral expectations.*

P_6: *The effects of self-efficacy on trying new technology are fully mediated by behavioral expectations.*

P_7: *The effects of attitudes on trying new technology are fully mediated by behavioral expectations.*

P_8: *The effects of subjective norms on trying new technology are fully mediated by behavioral expectations.*

P_9: *The effects of availability of information on trying new technology are fully mediated by behavioral expectations.*

Conclusion

This article highlights BE as a potentially effective (sole) predictor of consumers' initial trials of new technology. We argue how BE can help overcome the limitations of BI—in particular its temporal stability and predictive ability issues. Since BE has better temporal stability than BI, we propose that BE can offer a better predictor of new technology adoption. This improved temporal stability stems from BE's ability to take into account anticipated or unanticipated factors that may challenge actual behavior (Venkatesh et al. 2008). In addition, BE acknowledges a person's sense of control when performing the behavior, whereas as a sole predictor of behavior, BI cannot capture uncertainty or a sense of control (Warshaw and Davis 1985b). Prior studies in various contexts provide extensive evidence that researchers should use BE as a sole predictor of behavior instead of BI (e.g., Burgess et al. 2010; Gordon 1989, 1990; Mahardika et al. 2011; Rhodes and Matheson 2005). However, marketing researchers have overlooked BE thus far (see Table 2). We contend that BE deserves more attention as a mechanism to address some limitations of BI and better predict new technology adoption.

Our work also confirms the substantial importance of clearly defining the difference between the underlying mental judgments that form BE and those that form BI. Mental judgments that lead to BI generally are based on the desirability of the targeted behavior, whereas those for BE rely more on the feasibility of performing the targeted behavior (Fishbein and Stasson 1990). When a researcher asks BI questions, a respondent makes an estimation about whether adopting the new technology is desirable; if a researcher instead asks BE questions, the respondent should consider whether it is feasible or unfeasible for him or her to adopt the new technology, on the basis of the available resources and foreseeable challenges. For example, adopting 3D television might be desirable if the consumer's motivation is to provide the best family entertainment, and this desire is either feasible or unfeasible, depending on the availability of resources and cost benefits. Thus the consistency between BE and actual behavior is stronger than that between BI and actual behavior.

As a theoretical contribution, we explain different conceptualizations of BE and BI in terms of consumers' adoption of new technology. As we mentioned previously, marketing researchers have largely been relying on BI to predict new technology adoption, such as in the widely used TAM. Yet the TAM presumes that when a person forms BI judgments, he or she expects no impediments (Bagozzi et al. (1992), whereas in some cases, consumers clearly foresee such impediments. In these conditions especially, BE is a far more robust predictor than BI (Bagozzi and Warshaw 1990).

Adoption of new technology also offers its own levels of efficacy. For example, individual consumers have more control over their decisions than users in an organization, and they enjoy the freedom to seek new technology that suits their needs. Intuitively, if behavior is not fully under the users' volitional control, BE should be a better immediate predictor of behavior (Warshaw and Davis 1985b). Counter intuitively, BE also may be a better predictor of behavior than BI even if the behavior is under volitional control, such as in the context of consumers' new technology adoption.

Furthermore, consumer and organizational adoption settings involve varying degrees of uncertainty in the decision-making process. Organizations adopt new technology that suits their needs and resources, not necessarily the individual users', which limits the number of options available to users. This limitation also reduces uncertainty in their decision-making, because some factors that influence decisions already are controlled by the organization. In contrast, consumers encounter more uncertainty as they attempt to deal with anticipated or unanticipated impediments that challenge their actual adoption. Because BE is a better predictor of technology adoption than BI when the degree of uncertainty is high (Venkatesh et al. 2008), it should be particularly effective in consumer settings but also in organizational settings marked by high uncertainty.

In light of the immediate need to test the proposition, a descriptive research to identify the relationships among constructs--which are mainly tentative and speculative, is seen as relevant. More specifically, it should employ a longitudinal design, where data collection will be conducted at multiple points to capture both initial and continued behavior. It is since the mechanism of behavior prediction can only be understood by investigating subject's behavior at multiple points in time. Among the alternative context for the longitudinal study could be the implementation of new technology, particularly in retail services around the world. A panel of respondents that have been selected and agreed to provide information at specified intervals over an extended period of time will be needed to test the proposition. This longitudinal design will track changes in their thoughts regarding prediction of behavior at multiple points in time, which enables us to measure changes in behavioral expectation, behavioral intention, and other constructs in the conceptual model. The respondents will give their response at three points in time, three months before the implementation of new technology, near the beginning of the implementation, and three months after the implementation.

Finally, this article provides marketers (e.g., retailers) with the basis for identifying whether BE or BI will provide them with a better immediate predictor of behavior in various technology adoption situations. Consumers confront abundant new technology options that are easy to obtain, such as by downloading applications directly to mobile devices. As the number of options increases, consumers face increasing challenges and uncertainty in their decision making, which in turn makes it more difficult for marketers to predict behavior, because the consumers' BI is changing rapidly over time. Marketers thus should employ BE and BI selectively when developing designs for their new technology or product, though because BE offers better temporal stability, it is likely more predictive than BI. However, the determination ultimately depends on the various factors and antecedents involved in the new technology adoption process. Therefore, marketers should investigate further the efficacy of seven key determinants of BE: experience, perceived behavioral control, facilitating conditions, self-efficacy, attitudes, subjective norms, and availability of information.

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