Going Beyond Intention: Integrating Behavioral Expectation Into the Unified Theory of Acceptance and Use of Technology

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Research on information technology (IT) adoption and use, one of the most mature streams of research in the information science and information systems literature, is primarily based on the intentionality framework. Behavioral intention (BI) to use an IT is considered the sole proximal determinant of IT adoption and use. Recently, researchers have discussed the limitations of BI and argued that behavioral expectation (BE) would be a better predictor of IT use. However, without a theoretical and empirical understanding of the determinants of BE, we remain limited in our comprehension of what factors promote greater IT use in organizations. Using the unified theory of acceptance and use of technology as the theoretical framework, we develop a model that posits 2 determinants (i.e., social influence and facilitating conditions) of BE and 4 moderators (i.e., gender, age, experience, and voluntariness of use) of the relationship between BE and its determinants. We argue that the cognitions underlying the formation of BI and BE differ. We found strong support for the proposed model in a longitudinal field study of 321 users of a new IT. We offer theoretical and practical IT implications of our findings.

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Introduction

For decades, the retrieval, analysis, sharing, and storage of information has been a mainstay in business and society. In recent years, the intensity of information needs has increased exponentially as technological advancements have made it possible to store more information in a greater variety of forms (e.g., images, audio, video, and sensor) than ever before (Agarwal & Dhar, 2014; *Economist*, 2010). The improved digital infrastructure (e.g., networks, processing power, and storage capacity) has facilitated a move toward an increasing use of such information to enable people to make faster, more accurate decisions in their work. Not surprisingly, these technology-enabled information processing capabilities have shown benefits across a variety of domains, including health (e.g., Sykes, Venkatesh, & Rai, 2011), politics (e.g., Hurwitz, 2012; Wattal, Schuff, Mandviwalla, & Williams, 2010), and business (e.g., Goes, 2014). For example, in the health care informatics domain, computerized physician order entry systems help reduce processing time and decrease the incidence of medical errors (Bates et al., 2001; Sykes et al., 2011). In the political science domain, analysis of vast amounts of voter information is enabling greater customization of political campaigns to identify the best channels through which to appeal to voters (Hurwitz, 2012). However, the benefits of the capabilities embedded in information technology (IT) accrue through actual utilization. Unfortunately, underutilization (e.g., lack of use, inefficient use) of IT is still a major problem in practice (Brown, Venkatesh, & Goyal, 2014; Chau & Hu, 2002; Sykes & Venkatesh, forthcoming; Thatcher, McKnight, Arsal, Baker, & Roberts, 2011; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Zhang, & Sykes, 2011). Recent academic and trade press articles have underscored the pervasiveness of this problem in organizations and society (Booker, Detlor, & Serenko, 2012; Cheung, Lee, & Lee, 2013; Kim, Chun, & Lee, 2014; Sun & Zhang, 2008).

Recognizing that underutilization of IT continues to be a barrier to realizing the benefits, information science scholars have called for research to examine the factors that influence the *use* of IT so as to facilitate better access to, and sharing and processing of, information (e.g., Booker et al., 2012; Cheung et al., 2013; Hu, Lin, & Chen, 2005; Kaba & Toure, 2014; Reimer, Hagedal, Wolf, & Bahls, 2011; Sun, 2012; Sun & Zhang, 2008). IT use is a key dependent variable at multiple levels of theorizing from the individual to the team to the firm because of its link to performance (Jasperson, Carte, & Zmud, 2005; Maruping & Magni, 2012; Sarker, Valacich, & Sarker, 2005; Venkatesh et al., 2003). For decades, researchers have sought to identify and understand what predicts and explains individuals' IT adoption and use (Venkatesh et al., 2003). Drawing on theories from social psychology (e.g., theory of reasoned action [TRA]; Fishbein & Ajzen, 1975), Davis, Bagozzi, and Warshaw (1989) proposed behavioral intention (BI) as a proximal determinant of IT use in their technology acceptance model (TAM). BI is defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw & Davis, 1985a, p. 214). Over the years, BI has become the most prevalent determinant of IT use in individual-level IT adoption and use models and studies (Venkatesh et al., 2003). Even models developed based on different theoretical paradigms and reference disciplines (e.g., expectation-disconfirmation theory, motivational model [MM], and decomposed theory of planned behavior [TPB]) have employed BI or conceptually similar constructs (e.g., information systems [IS] continuance intention) as determinants of IT use (Bhattacherjee, 2001; Venkatesh et al., 2003). Many researchers have even used BI as a surrogate for IT use (Hong, Thong, Wong, & Tam, 2001; Hu et al., 2005; Kaba & Toure, 2014; Thong, Hong, & Tam, 2002; Zhang & Sun, 2009). Such use of BI is highly consequential, considering IT use is often a surrogate for IT implementation success in organizations (DeLone & McLean 2003; Sia et al., 2009; Venkatesh et al., 2003). However, Venkatesh, Maruping, and Brown (2006) and Venkatesh, Brown, Maruping, and Bala (2008) highlighted several limitations of BI and called for future research to go beyond the *intentionality* framework in order to predict behavior (e.g., IT use) more accurately. Drawing on research in social psychology (Warshaw & Davis, 1984; Warshaw & Davis, 1985a, 1985b), Venkatesh et al. (2006, 2008) argued that *behavioral expectation* (BE)—a cognition that has probabilistic underpinnings regarding decisions about IT use—would better predict behavior by addressing the limitations of BI and the intentionality framework.

BE is defined as "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). Venkatesh et al. (2008) theorized that BI and BE would predict different types of IT use (i.e., duration, frequency, and intensity) using distinct, yet complementary, mechanisms. In a longitudinal study, they found that whereas BI was a better predictor of duration of use, BE was a better predictor of frequency and intensity of use. Overall, the inclusion of BE as a predictor of IT use substantially increased the variance explained in IT use (i.e., 65% as opposed to 52% reported in Venkatesh et al., 2003). Although the introduction of BE as a determinant has enriched our understanding of IT use, it offers little guidance for practitioners and academics about how to increase one's BE in the first place. Stated differently, without a theoretical and empirical understanding of the determinants of BE, the strongest predictor of IT use (Venkatesh et al., 2008), we remain limited in our comprehension of what factors promote IT utilization in organizations. Consequently, practitioners may not be able to develop actionable interventions to enhance IT utilization.

The purpose of this research is to integrate BE into the unified theory of acceptance and use of technology (UTAUT) so as to make the theory robust to both internal and external determinants that influence individuals' use of IT. Several cognitions have been previously identified as being important for the adoption and use of IT. UTAUT captures many of these key cognitions and related factors. Thus, building on Venkatesh et al. (2008), we integrate BE into UTAUT by proposing a theoretical model that posits two determinants of BE—*social influence* and *facilitating conditions*. In doing so, we build a holistic nomological network of IT use. The model also includes *gender*, *age*, *voluntariness of use*, and *experience* as moderators of the relationships between BE and its proposed determinants. We test the model in the context of a longitudinal field study of a newly implemented organization-wide system. The findings contribute to the literature in three important ways. First, by integrating BE into UTAUT, we develop a holistic nomological net, which incorporates internal and external factors that affect the use of IT to process information. This contributes to the information science literature by explicitly identifying cognitions that consider external influences on use. Much of the research continues to focus on the internal drivers of IT use (e.g., Cheung et al., 2013; Kaba & Toure, 2014; Sun & Zhang, 2008; Zhang & Sun, 2009). This is a significant extension to UTAUT, a theory that currently only provides a BI-centric understanding of IT use (Venkatesh et al., 2003). By incorporating consideration of probabilistic factors, the

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integrated model provides a holistic understanding of individuals' decisions to adopt and use IT. Second, we provide a theoretical explication of the psychological mechanisms linking the predictors in UTAUT to perceptions of BI vis-à-vis BE. Finally, we identify two determinants of BE and theorize how these determinants influence BE in concert with four key moderators from UTAUT. This presents a contribution to the information science and social psychology literatures, which have called for work to identify determinants of BE (Venkatesh et al., 2008).

Background

In this section, we discuss BI and BE, the core constructs of interest, and highlight the key theoretical distinction between them with a particular focus on how individuals form BE and BI to perform a target behavior. This discussion is followed by an overview of UTAUT, where we make the case for specific predictors having an influence on BE and BI through different theoretical mechanisms.

BE and BI

As noted earlier, BE is the subjective probability of performing a behavior based on an individual's cognitive appraisal of various behavioral determinants. These behavioral determinants can be volitional or nonvolitional in nature (Warshaw & Davis, 1984, 1985a, 1985b). Examples of volitional behavioral determinants include BI, various beliefs, and attitudes related to a target behavior. Examples of nonvolitional behavioral determinants include facilitating conditions and events that may promote or inhibit behavioral performance (Venkatesh et al., 2006; Warshaw & Davis, 1984). Venkatesh et al. (2006) noted that whereas volitional determinants, such as BI, act as motivational drivers to perform a target behavior, nonvolitional determinants, such as unanticipated situational and/or environmental factors that are external to an individual, contribute to the estimation of the probability of performing the behavior. These nonvolitional determinants inhibit or facilitate the performance of a behavior. BE utilizes this information about the external environment to determine the probability of engaging in a behavior. Venkatesh et al. (2008) noted that decision-making heuristics, such as mental simulation and extrapolation tactics, play an important role in combining external environmental information to make a usage decision. Hence, BE's ability to account for the influence of nonvolitional determinants makes it a relatively more accurate predictor of behavior, compared to BI, in certain contexts (Venkatesh et al., 2006, 2008).

Whereas BE reflects an estimated probability of performing a behavior, BI represents an individual's consciously formulated plan to perform a behavior (Ajzen, 1991; Venkatesh et al., 2006). In drawing conceptual distinctions between BI and BE, Venkatesh et al. (2006, p. 161) noted that BI has an *internal* orientation—that is, it is formed based on an "individual's general belief system that represents the internalized structure of his or her external world." In other words, BI represents an internally formulated behavioral commitment to perform a target behavior (Fishbein & Ajzen, 1975). This internal focus is reflected in the roots of the BI construct. Ryan (1958) proposed three factors that serve as a platform upon which intentions can be formed: *means-end relations*; *intrinsic interest*; and *situational fit*. *Means-end relations* refer to the anticipated consequences of performing a behavior. This parallels the concept of extrinsic motivation (Deci, 1975), in which anticipated consequences serve as the primary motivator. *Intrinsic interest* represents the enjoyment derived from performing a behavior (Vallerand, 1997). It relates more closely to behavior as an end state because the action is performed for its own sake and not in anticipation of the consequences. Finally, *situational fit* refers to the physical or social demands for a behavior. In this case, a behavior may be demanded by a particular environmental situation for which it is appropriate, or it may be expected by a group (e.g., other social entities).

The discussion just described suggests that BI and BE have different, perhaps complementary, foci with regard to key drivers of behavior. Importantly, the former represents an *internally formulated* behavioral commitment to perform a target behavior (Fishbein & Ajzen, 1975), whereas the latter takes into consideration *external* factors (in addition to the internal factors reflected in BI) in estimating the probability of behavioral performance (Warshaw & Davis, 1985b). More specifically, BI represents an *internal belief structure or schemata*, whereas BE represents both the internal belief structure *and* an individual's self-prediction of performing a behavior considering unanticipated and/or situational factors that are *external* to the individual (Boden, 1973; Warshaw & Davis, 1985b). Internal schema and external factors should not be confused with intrinsic and extrinsic motivations. Internal schema of beliefs represent individuals' internalized belief structure associated with the performance of a behavior. Both intrinsic and extrinsic motivations are part of individuals' internal schema of beliefs. The psychological mechanisms underlying the formation of BI in the technology adoption literature (Davis, Bagozzi, & Warshaw, 1992; Venkatesh & Davis, 2000; Venkatesh et al., 2003) are consistent with the three factors discussed earlier. *Performance expectancy*, an individual cognition about the expected consequences of using technology, is primarily an extrinsic motivation that captures the *means-end relations* (Davis et al., 1992; Venkatesh et al., 2003). *Intrinsic interest* is captured through *enjoyment* and *playfulness* (Davis et al., 1992; Venkatesh & Bala, 2008). Finally, *situational fit* is captured through *social influence* and *facilitating conditions* (Taylor & Todd, 1995a, 1995b; Venkatesh et al., 2003). Of the three factors proposed by Ryan (1958), the first two represent the cognitive and affective aspects of an individual's internal belief structure or schema. The third factor primarily represents external aspects of an individual's belief structure. However, as we will argue, situational factors—that is, social influence and facilitating conditions—can have both internal and external facets but *only* the internal facets will

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play an important role in the formation of BI. In contrast, the external facets are expected to be linked to the formation of BE. In order to further elucidate the linkages between technology adoption predictors and BI and BE, we briefly discuss the key constructs underlying UTAUT next. We then develop our hypotheses, expounding upon the theoretical mechanisms linking UTAUT to BI versus BE.

UTAUT

UTAUT was formulated as an integrated model of IT adoption and use by synthesizing eight major theories/models employed in past research (Venkatesh et al., 2003). The eight theories/models are: TRA (Fishbein & Ajzen, 1975), TAM (Davis et al., 1989), MM (Davis et al., 1992), TPB (Ajzen, 1991; Taylor & Todd, 1995a), combined TAM and TPB (Taylor & Todd, 1995a, 1995b), model of PC utilization (Thompson, Higgins, & Howell, 1991), innovation diffusion theory (Moore & Benbasat, 1991), and social cognitive theory (Compeau & Higgins, 1995). Through longitudinal field studies at six organizations, Venkatesh et al. (2003) empirically compared the different models. Based on a theoretical and empirical synthesis, they presented three predictors of BI: *performance expectancy*; *effort expectancy*; and *social influence*. BI and *facilitating conditions* were the predictors of technology use. They incorporated up to four moderators—that is, *gender*, *age*, *voluntariness*, and *experience*—of the relationships theorized in UTAUT.

Performance expectancy is defined as "the degree to which an individual believes that using a system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). UTAUT theorized and found that the relationship between performance expectancy and behavioral intention was moderated by gender and age, such that the effect was stronger for men and, more specifically, younger men. *Effort expectancy* is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). UTAUT theorized and found that the relationship between effort expectancy and behavioral intention was moderated by gender, age, and experience, such that the effect was stronger for women, particularly older women, and even more so when they had limited experience with the system. *Social influence* is defined as "the degree to which an individual perceives that important others believe that he or she should use the new system" (Venkatesh et al., 2003, p. 451). UTAUT theorized and found that the effect of social influence on behavioral intention was moderated by gender, age, voluntariness, and experience, such that the effect was strongest for older women in mandatory contexts with limited experience. *Facilitating conditions* is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). Consistent with past research, UTAUT theorized and found BI to be a determinant of system use at all points in time. Furthermore, UTAUT theorized and found that facilitating conditions has a direct influence on system use and this influence was moderated by age and experience, such that the effect was stronger for older people with increasing experience with the target system.

Theory

In this section, we develop the theoretical rationale for our research model shown in Figure 1. In addition to the UTAUT relationships, we include several TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) relationships in our model in order to form a complete nomological net of IT adoption. We expect that the UTAUT, TAM2, and TAM3 relationships will hold in our model. We do not hypothesize these relationships here because they have been hypothesized and supported in past research (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Thus, we focus on hypothesizing new relationships and, where relevant, revisit existing relationships, but refine the underlying psychological mechanisms by emphasizing that only the *internal facets* of different behavioral determinants drive the formation of BI and the *external facets* of different behavioral determinants will influence the formation of BE. Additionally, because BE reflects consideration of internal and external factors, we emphasize that internal facets will influence BE through their effects on BI (Venkatesh et al., 2008).

Performance expectancy, effort expectancy, and social influence as predictors of BI

Performance expectancy and effort expectancy, two important predictors of BI, represent an individual's cognitions about the performance gains and the amount of effort associated with the use of a technology (Venkatesh et al., 2003). These cognitions are a fundamental part of the internal belief structure upon which an individual's BI is formed. Therefore, consistent with UTAUT, we expect performance expectancy and effort expectancy to positively influence BI, moderated by gender, age, and/or experience. Previous research has also found a positive relationship between effort expectancy and performance expectancy (Venkatesh & Davis, 2000).

Social influence is another important predictor of BI. Past research has argued that social influence shapes individuals' BI to use a system (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Similar to performance expectancy and effort expectancy, social influence is viewed as shaping the internal belief structure upon which individuals' BI is formed. This internal orientation of social influence is reflected in individuals' belief that using the system will enhance their own status in the eyes of important others who believe the system should be used (Kaba & Toure, 2014; Pelling & White, 2009; Venkatesh & Davis, 2000). Consistent with this logic, previous empirical studies support the relationship between social influence and BI across a variety of information technologies (e.g., Brown, Dennis, & Venkatesh, 2010; Gallivan, Spitler, & Koufaris, 2005; Kaba & Toure, 2014;

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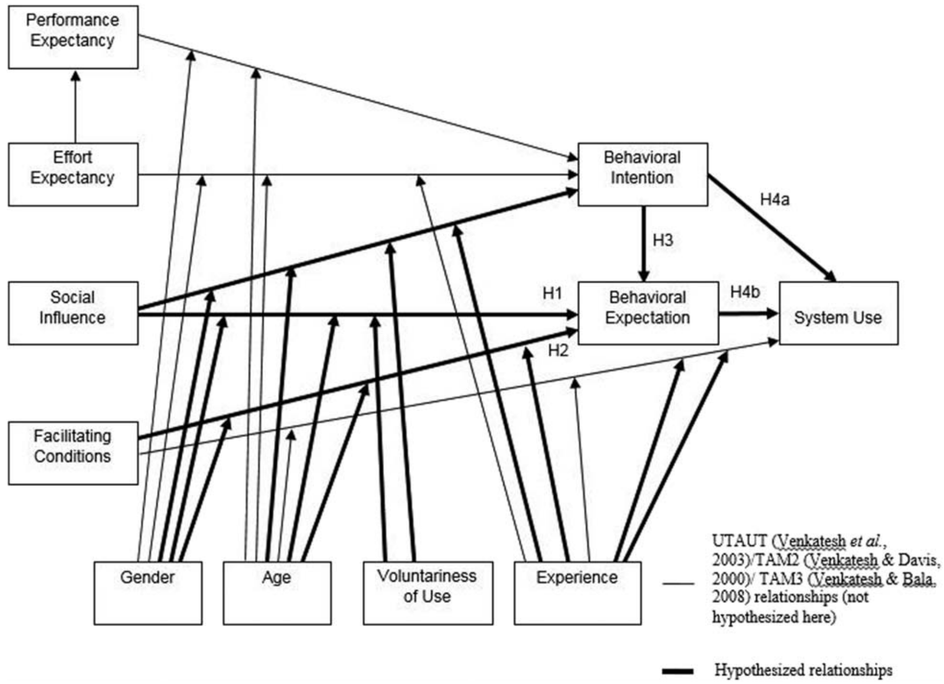

FIG. 1. Research model.

Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). Consequently, we expect social influence to be associated with BI, and moderated by age, gender, voluntariness, and experience.

Social influence

Although it is well established that social influence affects use by shaping BI, we also believe that it has an external orientation that should influence BE. Fundamentally, social influence reflects the weight that one places on the views of external others (as opposed to one's own view) regarding use of the system. Consideration of the views of an important external referent should factor into an individual's self-estimated probability of using the system (Venkatesh et al., 2006; Warshaw & Davis, 1985a). Pressure from important external referents, such as supervisors or coworkers, can result in a greater self-estimated probability of using the system as an individual seeks to comply with their expectations. This is especially true because many work processes have dependencies that involve information from employees with different roles (Maruping & Magni, 2015). Systems often have these dependencies built into the information flow, such that a supervisor cannot create a complete report if information is not entered into the system by employees. In light of such common work process dependencies, individuals anticipate that they will comply with any perceived pressure from external others, if only to avoid reprimand. Such considerations constitute an important part of the environment in which individuals estimate their subjective probability of using the system by BE.

We expect that gender, age, and voluntariness will moderate the social influence/BE relationship. Venkatesh and Morris (2000) suggested that women are more likely to comply with organizational directives, whereas men are more likely to rebel. Women prefer to select actions with a greater probability of approval by external others (Barnett & Karson, 1989). In mandatory contexts, women are more likely to comply with organizational or supervisory mandates than are men. Therefore, we expect the effect of social influence on BE to be more pronounced among women. Similarly, older individuals are more likely than younger individuals to comply with social influence (Overby, 2002). Although past research has suggested that social influence will attenuate over time because increasing experience provides a more instrumental basis for IT use (Hartwick & Barki, 1994; Venkatesh & Davis, 2000), we argue that experience will not moderate the social influence/BE relationship because individuals' BE to comply with normative pressures will not attenuate over time. For example, when users are required to use a system, even if they believe that the system does not provide any instrumental benefits, they still will expect to use it. Based on the arguments outlined earlier, we theorize that the effect of social influence on BE will be more important for women, particularly older women, in mandatory settings.

H1: The effect of social influence on BE will be moderated by gender, age, and voluntariness, such that the effect will be stronger for women, particularly older women in mandatory settings.

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Facilitating conditions

As noted by Venkatesh et al. (2008), IS (e.g., Taylor & Todd, 1995a,b) and social psychology (e.g., Armitage & Conner, 1999) research has conceptualized and operationalized facilitating conditions using two or more constructs to represent the internal and external facets separately. They further suggested that the internal facets of facilitating conditions operate through effort expectancy, which directly influence BI. In UTAUT, Venkatesh et al. (2003) reason that effort expectancy and performance expectancy capture the effects of the internal facets of facilitating conditions. Venkatesh et al. (2003) conclude that the external facets of facilitating conditions—that is, those pertaining to the availability of resources and support—should not influence BI. Venkatesh et al. (2008) reinforce this idea, noting that UTAUT's conceptualization of facilitating conditions emphasizes external facets and, as such, is not related to the internally oriented BI. Consistent with Venkatesh et al. (2003, 2008), we do not hypothesize a direct relationship between facilitating conditions and BI.

Facilitating conditions capture the objective factors in the environment that affect an individual's likelihood of using the system (Mathieson, Peacock, & Chin, 2001; Thompson et al., 1991; Venkatesh et al. 2003). These objective factors are external to the individual and constitute enablers and/or impediments that can affect whether or not system use occurs (Warshaw & Davis, 1985a, 1985b). Facilitating conditions are likely to tap into BE because they represent those aspects of the external environment that can enable an individual to use the system. As noted earlier, BE with its external focus, incorporates such information when estimating the subjective probability of using the system (Venkatesh et al., 2008). That is, as individuals estimate their subjective probability of using the system, they consider the extent to which the environment provides support by way of resources and guidance that promote use. The greater the level of support present in the environment, the greater the individual's estimated probability of using the system. Conversely, if the environment lacks the necessary resources (e.g., help desk, reference guide, sufficient processing power, or fast network connection speed) to support use, an individual is likely to form a lower estimate of the probability of using the system.

Past research suggests that women tend to be more process oriented in their approach to using new systems (Venkatesh, Morris, & Ackerman, 2000). They tend to benefit most from receiving support as they work through the process of using the system. The availability of user guides and system-related expertise can therefore be an important determinant of their expectation to use the system. This is expected to be particularly true among older women given that the ability to learn complex new systems becomes increasingly effortful over time as old knowledge structures become heavily engrained (Morris & Venkatesh, 2000). Older individuals tend to place a heavier emphasis on the role of external factors in determining whether to perform complex behaviors such as system use (Morris & Venkatesh, 2000). Such individuals' BE regarding use is likely to be predicated on the availability of resources to support their system usage efforts. We also expect that, with increasing experience, older women will more strongly emphasize access to facilitating conditions. With increasing experience, such individuals become familiar with the necessary avenues to access help when using the system. This ease of accessibility to supporting resources will factor into their subjective probability of using the system. In sum, we expect that the effects of facilitating conditions on behavioral expectation will be moderated by gender, age, and experience as facilitating conditions will be more important to women, older individuals, and individuals with more experience with a system.

H2: The influence of facilitating conditions on BE will be moderated by gender, age, and experience, such that the effect will be stronger for women, particularly older women, in the later stages of experience.

BI

Consistent with Venkatesh et al. (2008), we hypothesize that BI will positively influence BE. In theorizing this relationship, Venkatesh et al. (2008, p. 486) underscored the "temporal sequencing of events leading up to the execution of a target behavior." They suggested that individuals form the perception of BI first as BI represents an "internal determination to perform a behavior." This reflects the culmination of all of the internal facets that shape behavior. Subsequently, individuals' perceptions incorporate various external factors that can potentially impede the successful execution of a behavior—that is, the formation of BE. This suggests that unless individuals develop the internal determination to perform a behavior—that is, BI—it is unlikely that they will even consider the external impediments to perform the behavior. In other words, perception of BI will lead to formation of BE. This further reinforces the idea that BE reflects both internal and external factors in predicting behavior.

H3: BI will positively influence BE.

Predicting system use

Although our key focus is to understand the determinants of BE, we include system use in our model to have a complete nomological network of IT adoption and use (Venkatesh et al., 2003). Consistent with Venkatesh et al. (2006, 2008), we hypothesize that the effects of BI and BE on system use will be moderated by experience, such that the effect will be stronger for BI and weaker for BE. Venkatesh et al. (2008) argued that, with increasing experience, individuals are able to form more accurate, comprehensive, and stable BI as their motivations incorporate external factors related to system use. In such situations, BE will have limited predictive ability over and above BI to explain system use (Venkatesh et al., 2008).

TABLE 1. Principal components analysis with direct oblimin rotation.

Items			Loadings					
Performance expectancy (PE)	PE1	I would find the system useful in my job.	**0.84**	0.05	0.06	0.20	0.17	0.21
	PE2	Using the system enables me to accomplish tasks more quickly.	**0.82**	0.25	0.28	0.05	0.13	0.14
	PE3	Using the system increases my productivity.	**0.88**	0.09	0.23	0.23	0.21	0.20
	PE4	If I use the system, I will increase my chances of getting a raise.	**0.84**	0.11	0.13	0.16	0.12	0.17
Effort expectancy (EE)	EE1	My interaction with the system would be clear and understandable.	0.12	**0.92**	0.09	0.19	0.20	0.13
	EE1	It would be easy for me to become skillful at using the system.	0.24	**0.91**	0.06	0.25	0.24	0.20
	EE3	I would find the system easy to use.	0.20	**0.89**	0.19	0.11	0.21	0.14
	EE4	Learning to operate the system is easy for me.	0.09	**0.88**	0.16	0.12	0.17	0.16
Social influence (SI)	SI1	People who influence my behavior think that I should use the system.	0.24	0.11	**0.81**	0.07	0.15	0.12
	SI2	People who are important to me think that I should use the system.	0.21	0.02	**0.85**	0.16	0.19	0.13
	SI3	The senior management of this business has been helpful in the use of the system.	0.22	0.02	**0.78**	0.06	0.22	0.15
	SI4	In general, the organization has supported the use of the system.	0.14	0.07	**0.71**	0.07	0.21	0.08
Facilitating conditions (FC)	FC1	I have the resources necessary to use the system.	0.15	0.12	0.20	**0.84**	0.22	0.14
	FC2	I have the knowledge necessary to use the system.	0.24	0.15	0.21	**0.83**	0.27	0.23
	FC3	The system is not compatible with other systems I use.	0.17	0.13	0.06	**0.72**	0.29	0.27
	FC4	A specific person (or group) is available for assistance with system difficulties.	0.19	0.24	0.20	**0.73**	0.28	0.22
Behavioral intention (BI)	BI1	I intend to use the system in the next <n> months.	0.12	0.17	0.19	0.22	**0.81**	0.14
	BI2	I predict I would use the system in the next <n> months.	0.17	0.19	0.14	0.16	**0.88**	0.26
	BI3	I plan to use the system in the next <n> months.	0.22	0.13	0.05	0.13	**0.85**	0.27
Behavioral expectation (BE)	BE1	I expect to use the system in the next <n> months.	0.22	0.13	0.15	0.17	0.23	**0.84**
	BE2	I will use the system in the next <n> months.	0.25	0.12	0.17	0.19	0.25	**0.87**
	BE3	I am likely to use the system in the next <n> months.	0.17	0.19	0.15	0.13	0.21	**0.82**

H4a: The influence of behavioral intention on use will be moderated by experience, such that with increasing experience with the target system the effect will become stronger.
H4b: The influence of behavioral expectation on use will be moderated by experience, such that with increasing experience with the target system the effect will become weaker.

Methods

To test the research model, we conducted a longitudinal field study in an organization that was implementing a new IS. The study spanned 12 months and included data collection at five periods of time. The sample, measurement, and data collection procedure are described here.

Sample

Employees of a large telecommunications firm that was introducing a significant new IS participated in the study. The organization was implementing a web-based decision support and transactional system in three of its business units. The system would support information retrieval for decision support, data entry and storage for financial and other transactions, and data sharing across functional business areas. The use of the new IS was voluntary. Of the nearly 918 total employees in the organization, 720 participated in the study. Forty-five percent of the participants provided usable responses at all five points of measurement, resulting in a final sample size of 321. The response rate was quite high given the duration of the study. One hundred and ten of the participants in the final sample were women (34%). The participants had an average age of 37.2 with a standard deviation (SD) of 9.5. The participants were from all levels of the organizational hierarchy. In order to determine whether nonresponse bias was a concern in the sample, we compared the participants who responded at all measurement points to nonrespondents on the demographic variables used here—namely, gender and age. No significant differences were found. There were 35% women and an average age of 39.6 (standard deviation of 10.1) among nonrespondents.

Measurement

All constructs were operationalized using validated items (see Table 1). Specifically, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention were measured using scales from Venkatesh et al. 2003. BE was measured using a four-item scale from Venkatesh et al. (2006, 2008). The constructs were measured on a 7-point Likert-type scale using *strongly disagree* and *strongly agree* as anchors. The measurement of gender, age, experience, and voluntariness was consistent with Venkatesh et al. (2003). System use was measured using three items from Venkatesh et al. (2008)—frequency of use, duration of use, and intensity of use. Because these three items were measured on different scales, we normalized by computing z-scores.

Data collection procedure

Employees were educated about the new IS through organization-sponsored training programs. Training materials were tailored for different job types and were developed by a training company that worked in conjunction with the

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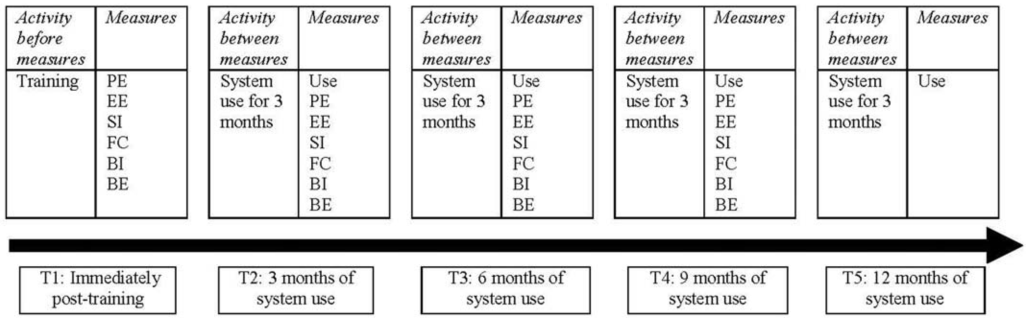

FIG. 2. Summary of study design with points of measurement.

designers and developers of the new IS. Immediately post-training, employees filled out a questionnaire that included items to measure the UTAUT predictors as well as their BI and BE to use the new IS. Because of the longitudinal design of the study, it was necessary to track specific respondents over time. To accomplish this, unique bar codes were printed on each survey, allowing specific responses to be tracked over time. Every 3 months for the next 6 months, employees responded to a survey. The purpose of this time table for survey administration was twofold. First, it enabled us to track the stability of the UTAUT constructs as well as BE over the course of the study period. Second, past research has shown that BI and BE exhibit different levels of predictive validity over time (Venkatesh et al., 2006). Conducting multiple measurements over time allowed us to control for such variations in predictive validity. Figure 2 illustrates the study design.

Results

We performed a factor analysis using direct oblimin rotation. Table 1 presents the results of the factor analysis. As Table 1 illustrates, each item loaded on the intended construct and all item loadings were greater than 0.70, providing support for convergent validity. The internal consistency reliabilities for all constructs were greater than 0.70 in all time periods, further supporting convergent validity. In addition, all of the item cross-loadings were less than 0.26, indicating discriminant validity. To further assess convergent and discriminant validity, we examined the square roots of the shared variance between the constructs and their measures. These were found to be higher than the correlations across constructs, thus supporting convergent and discriminant validity (Fornell & Larcker, 1981). The correlations and descriptive statistics are shown in Table 2.

Our research design involved measurement of system use, BE, BI, and the UTAUT predictors at four different time periods. Consequently, it was necessary to account for within-subject correlations between measurement points when estimating the coefficients. We accomplished this by using a generalized estimating equations (GEE) approach to test the model (Ballinger, 2004; Pluye et al., 2013; Zeger & Liang, 1986). GEE accounts for the correlations between multiple measurements in longitudinal research designs and can be used to test main and interaction effects (Ballinger, 2004; Pluye et al., 2013). We specified an unstructured correlation model whereby the observations across each time period are allowed to freely correlate within subjects (Fitzmaurice, Laird, & Rotnitzky, 1993). This is the preferred

TABLE 2. Descriptive statistics and correlations.

	Cronbach's alpha	Mean	SD	1	2	3	4	5	6	7	8	9	10
1.GDR	NA	NA	NA										
2.AGE	NA	37.2	9.5	0.21**									
3.VOL	0.91	4.77	1.39	0.14*	−0.13*								
4.EXP	NA	NA	NA	0.04	0.05	0.08							
5.PE	0.88	4.13	1.19	0.26**	−0.21*	0.23**	0.25**	.					
6.EE	0.91	4.21	1.13	0.28**	−0.29**	0.08	0.29**	0.41**	.				
7.SI	0.83	4.51	1.04	−0.23**	0.34**	−0.32**	−0.19*	0.33**	0.17*	.			
8.FC	0.77	3.22	1.26	0.19*	−0.28**	0.21**	0.21**	0.19*	0.26*	0.13*	.		
9.BI	0.89	4.07	1.11	0.26**	−0.30**	0.10	0.19*	0.46**	0.24**	0.19*	0.26**	.	
10.BE	0.87	4.37	1.12	0.24**	−0.26**	−0.16*	0.24**	0.18*	0.22**	0.51**	0.42**	0.46**	.
11.USE	NA	4.31	1.31	0.31**	−0.34**	−0.14*	0.29**	0.44**	0.28**	0.30**	0.33**	0.60**	0.71**

Note. GDR, gender; VOL, voluntariness; EXP, experience; PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; BI, behavioral intention; BE, behavioral expectation; USE, system use; NA, not applicable. $p < 0.05$; $*p < 0.01$; $**p < 0.001$.

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TABLE 3. GEE model testing results.

	BI		BE		Use	
	D	D+I	D	D+I	D	D+I
R^2	0.41	0.73	0.59	0.76	0.40	0.62
ΔR^2		0.32**		0.17**		0.22**
Akaike information criterion (AIC)	4,320.11	980.65	3,890.56	845.24	3,389.03	1,140.41
Behavioral intention (BI)			0.33**	0.28**	0.17*	0.16*
Performance expectancy (PE)	0.55**	0.14*				
Effort expectancy (EE)	0.07	0.06				
Social influence (SI)	0.08	0.05	0.32**	0.10		
Facilitating conditions (FC)	0.10	0.09	0.34**	0.13*	0.06	0.06
Behavioral Expectation (BE)					0.47**	0.05
Gender (GDR)	0.08	0.07	0.07	0.07		
Age (AGE)	−0.07	−0.06	−0.08	−0.05		−0.07
Voluntariness (VOL)	0.10	0.06	−0.03	−0.02		
Experience (EXP)	0.06	0.06		0.03		0.05
PE X GDR		−0.05				
BI X EXP						0.37**
BE X EXP						−0.42**
PE X AGE		−0.08				
GDR X AGE[a]		0.07		0.00		
PE X GDR X AGE		0.51**				
EE X GDR		0.02				
EE X AGE		0.06				
EE X EXP		0.04				
GDR X AGE (included earlier)		[a]		[a]		
GDR X EXP[b]		0.08		0.07		
AGE X EXP[c]		−0.13*		0.04		0.04
EE X GDR X AGE		−0.09				
EE X GDR X EXP		0.10				
EE X AGE X EXP		0.14*				
GDR X AGE X EXP[d]		−0.10		0.13*		
EE X GDR X AGE X EXP		−0.31**				
FC X GDR				0.05		
FC X AGE				0.10		0.13*
FC X EXP				0.03		0.08
SI X GDR		0.07		0.08		
SI X AGE		0.08		0.03		
SI X VOL		0.10		0.10		
SI X EXP		−0.13*				
GDR X AGE (included earlier)		[a]				
GDR X VOL		0.08		0.07		
GDR X EXP (included earlier)		[b]		[b]		
AGE X VOL		0.10		0.02		
AGE X EXP (included earlier)		[c]		[c]		
VOL X EXP		0.11*				
FC X GDR X AGE				0.02		
FC X GDR X EXP				0.01		
FC X AGE X EXP				0.11*		0.06
SI X GDR X AGE		−0.12*		0.04		
SI X GDR X VOL		0.08		0.11*		
SI X GDR X EXP		0.05				
SI X AGE X VOL		0.07		0.05		
SI X AGE X EXP		0.09				
SI X VOL X EXP		0.08				
GDR X AGE X VOL		0.05		0.07		
GDR X AGE X EXP (included earlier)		[d]				
GDR X VOL X EXP		0.10				
AGE X VOL X EXP		0.12*				
SI X GDR X AGE X VOL		0.08		0.29**		
SI X GDR X AGE X EXP		−0.12*				
SI X GDR X VOL X EXP		−0.12*				

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TABLE 3. *Continued*

	BI		BE		Use	
	D	D+I	D	D+I	D	D+I
SI X AGE X VOL X EXP		−0.05				
FC X GDR X AGE X EXP				0.29**		
GDR X AGE X VOL X EXP		−0.05				
SI X GDR X AGE X VOL X EXP		−0.24**				

Notes. D, direct effects only; D + I, direct effects and interaction terms. "Included earlier" indicates that the term has been listed earlier in the table, but is included again for completeness as it relates to higher order interaction terms being computed. [a] indicates that the GDR X AGE term was included earlier, [b] indicates that the GDR X EXP term was included earlier, [c] indicates that the AGE X EXP term was included earlier, and [d] indicates that the GDR X AGE X EXP term was include earlier. $p < 0.05$; $*p < 0.01$; $**p < 0.001$.

approach to modeling the within-subject correlations because it does not force a particular correlation structure on the data, but rather allows the structure to emerge from the data (Ballinger, 2004). We report the Akaike information criterion (AIC) as an assessment of model fit in GEE. AIC is a robust approach to evaluating model fit because it encompasses the trade-off between model fit and model complexity by penalizing models that incorporate numerous variables with limited predictive validity (Akaike 1974). Lower AIC values indicate better model fit. In our analysis, gender was coded using a dichotomous dummy variable, age was coded as a continuous variable, voluntariness was coded per the score for each participant, and experience was coded as an ordinal variable. Also, given that experience was mapped to the point of measurement, thus representing time, it was included as a way of linking observations of different individuals over time. We mean centered the variables before creating the interaction terms so as to reduce the potential for multicollinearity (Aiken & West, 1991). The variance inflation factors were well below the recommended cut-off value of 10 (Ryan, 1997), suggesting that multicollinearity was not a major concern in the analyses.

Table 3 shows the detailed model test results for BI, BE, and system use, respectively. Our research model explained between (i) 40% and 74% of the variance in BI, (ii) 58% and 78% of the variance in BE, and (iii) between 39% and 63% of the variance in system use. In each case, the AIC for the model with interaction effects is a better fit to the data than the model that only includes direct effects.

Consistent with Venkatesh et al. (2003), performance expectancy had a positive main effect on BI and the main effect of effort expectancy and social influence was nonsignificant. Table 3 shows that the three-way interaction among performance expectancy, gender, and age was significant. Specifically, the three-way interaction term suggests that the effect of performance expectancy on BI was more important for younger men, consistent with past research (Warshaw, 1980). Similarly, Table 3 shows that the four-way interaction of effort expectancy, gender, age, and experience was significant, with the effect of effort expectancy on BI being stronger for older women with less experience with the system. The five-way interaction between social influence, gender, age, experience, and voluntariness was significant, suggesting that the effect of social influence on BI was stronger for older women with limited experience in mandatory contexts. Taken together, these results are largely consistent with the original tests of UTAUT conducted by Venkatesh et al. (2003).

In H1, we predicted that the effect of social influence on BE would be moderated by gender, age, and voluntariness. Table 3 shows a significant positive main effect of social influence on BE. In addition, the results of the model with interaction effects show that the four-way interaction term was significant, indicating that the effect of social influence on BE was stronger for older women with limited experience with the system in mandatory contexts. This provides support for H1.

H2 suggested that the effect of facilitating conditions on BE would be moderated by gender, age, and experience. As shown in the main effects model in Table 3, facilitating conditions had a positive and significant main effect on BE. The interaction model in Table 3 shows that the four-way interaction term was significant. Specifically, the effect was stronger for older women with increasing experience. Therefore, H2 is supported. H3 predicted that BI would directly influence BE. As the main effects model in Table 3 shows, the coefficient for BI was significant, thus supporting H3. Finally, the interaction model in Table 3 shows that with increasing experience, the effect of BI on system use was stronger and the effect of BE on system use was weaker, thus supporting H4a and H4b.

Discussion

The objective of this research was to extend information science research by integrating the role of BE as an externally oriented predictor of IT use and identifying its antecedents. BE was recently introduced as an important predictor of IT adoption and use (Venkatesh et al., 2008). Building on research that found BE to be the strongest predictor of system use, we identified two key determinants of BE—social influence and facilitating conditions—using UTAUT as the theoretical foundation. We also extended UTAUT by integrating BE and providing a complete nomological net of IT adoption and use. To the best of our knowledge, this is one of the earliest studies to examine the antecedents of BE in

TABLE 4. Summary of findings.

Hypothesis no.	Dependent variables	Independent variables	Moderators	Result	Explanation
H1	Behavioral expectation	Social influence	Gender, age, voluntariness	Supported	Effect stronger for women, older workers, under conditions of mandatory use
H2	Behavioral expectation	Facilitating conditions	Gender, age, experience	Supported	Effect stronger for women, older workers with increasing experience
H3	Behavioral expectation	Behavioral intention	None	Supported	Behavioral intention had a positive influence on behavioral expectation.
H4a	System use	Behavioral intention	Experience	Supported	Effect stronger with increasing experience
H4b	System use	Behavioral expectation	Experience	Supported	Effect weaker with increasing experience

IT adoption and use contexts. We theorized that BE captures the influence of external factors (e.g., situations and/or environmental factors) that may augment or inhibit one's ability to perform a desired behavior (e.g., IT use). Our results supported this argument by demonstrating a relationship between social influence, facilitating conditions, and BE. These results suggest an expanded role for the UTAUT determinants as being both internal and external motivators of behavior. We found strong support for our model explaining 74% of the variance in BI, 78% in BE, and 64% in system use. Table 4 provides a summary of our findings.

Theoretical contributions

This research makes four important theoretical contributions. First, we contribute to the information science literature on IT adoption and use. Research on IT adoption and use in information science continues to focus primarily on internally oriented predictors such as BI. Identification of antecedents and elaboration of their relationship with BI has also followed this internal orientation, as evidenced by information science research on the role of attitudes (e.g., Sun & Zhang, 2008; Zhang & Sun, 2009), satisfaction (e.g., Cheung et al., 2013), and BI determinants in UTAUT (e.g., Kaba & Toure, 2014). We extend this stream of research by introducing the role of BE as an externally oriented predictor of IT use. This is a significant advancement to the information science literature because it demonstrates that the use of systems that support information processing (e.g., information seeking, retrieval, and storage) is not only determined by users' internal motivations, but also involves consideration of external influencers that can facilitate or impede such use. Our research demonstrates that such consideration is particularly important in predicting IT use at one of the most critical stages of adoption—namely, when users are inexperienced with the system.

The second contribution is the development of a holistic nomological net of IT adoption by incorporating BE and its determinants into UTAUT and the research model proposed by Venkatesh et al. (2008). Whereas Venkatesh et al. (2003) note that we might have approached the practical limits of our ability to explain IT adoption, our findings suggest that there is still room for theoretical advancement in IT adoption research and models. The current study advances IT adoption research and adds richness to IT adoption models by developing and testing a nomological net of IT adoption that incorporates BE and its determinants. This is a significant extension to Venkatesh et al.'s (2003) theory—UTAUT—that only provides a BI-centric understanding of IT adoption. The integrated model proposed here provides a holistic understanding of individual-level IT adoption and use in organizations.

This holistic, integrated model further contributes to the literature by delineating the internal versus external facets of the UTAUT predictors. We provided theoretical explanations of how the internal facets of UTAUT predictors would influence BI, which has an internal orientation, and the external facets would influence BE, which incorporates external factors associated with performing a behavior. In particular, we argued that an internally oriented set of mechanisms—performance expectancy and effort expectancy—influenced BI whereas an externally oriented mechanism—facilitating conditions—influenced BE in UTAUT. Additionally, we argued that social influence plays a dual role as an internally and externally oriented mechanism that influences BI and BE. Our results indicate that social influence had a main effect on BE (but not BI) at all time periods. This is consistent with our argument that social influence reflects an external orientation that captures the influence of external (to the individual) referents regardless of the level of experience. In contrast, past research has found the link between social influence and BI to weaken with increasing experience with a system (Karahanna, Straub, & Chervany, 1999; Venkatesh & Davis, 2000). We also argued and found that the moderators of the social influence/BE relationship would be different from those playing a role in the social influence/BI relationship, further reinforcing differences in the role of social influence as an internally versus externally oriented mechanism.

A final contribution is the identification of two key determinants of BE. Although past research has examined the relationship between BE and behavior (e.g., Venkatesh et al., 2006, 2008; Warshaw & Davis, 1984, 1985a, 1985b), none so far have really focused on identifying and testing the determinants of BE. Using UTAUT, which is an integrated model of IT adoption, as the theoretical framework, we identified two determinants of BE—that is, social influence and facilitating conditions—and developed theoretical arguments of how and why these determinants would influence BE. We also included four moderators from UTAUT—that is, gender, age, experience, and voluntariness of use—and discussed how these moderators would influence the relationship between BE and its determinants. The identification and empirical validation of the determinants of BE and their moderators represents a significant contribution to the information science literature.

Limitations and future research directions

Our findings should be interpreted in light of the limitations of the research. One key limitation is that even though we argued that the internal facets of various determinants will influence BI and that the external facets will influence BE, we did not measure these facets explicitly. Whereas facilitating conditions were operationalized with a more external orientation, the operationalization of social influence did not provide any indication of whether it was internal or external. It is therefore critical to focus on research that will help confirm that the proposed mechanisms are indeed at play and rule out potential competing explanations. Experimental research will be important in order to accomplish this. This research can also be used to study the impact of managerial and training interventions on the various key constructs in the model (Venkatesh & Bala, 2008).

Although we have presented theoretical arguments about the internal and external facets of these constructs, future research should empirically examine how specific normative and control beliefs tie into the internal and external facets. For instance, although we argued that social influence plays a role as an internally and externally oriented mechanism, we did not elaborate the specific means by which it affects BI versus BE. Past research has suggested that social influence affects behavior through compliance, internalization, and identification (Kelman, 1958, 1961; Venkatesh & Davis, 2000). It is possible that social influence affects BE through compliance and affects BI through internalization and identification. Empirical research is needed to validate this. Similarly, control beliefs and their ties to the internal and external facets of facilitating conditions should be considered carefully. For example, in order to be faithful to UTAUT, we included the same items—however, one of those items refers to knowledge, an internal facet. Concerns related to this are somewhat alleviated given that the three other items related to external facets and the knowledge item were highly correlated with the external facets. Future research should certainly revisit and refine this. Greater attention should be paid to these mechanisms given that the importance of their internal and external facets may differ according to the specific behavior of interest or the context in which the behavior is studied. Similarly, the internal and external facets of social influence and facilitating conditions should be operationalized to examine how they influence BI and BE.

Whereas the current work provided empirical support for the need to broaden the predictors of behavior, the findings at this point are limited to the IT adoption context. Future work should examine the generalizability of these findings through a careful review and empirical examination of research in other behavioral domains and contexts, such as organizational behavior and psychology. For example, Warshaw and Davis (1984) suggested that factors such as habit and individual abilities may be determinants of BE. However, such factors were never theorized or tested as predictors of BE. Furthermore, researchers should develop models predicting BE in various domains, such as IT adoption in homes (e.g., Brown & Venkatesh, 2005) and groups (Maruping & Magni, 2012, 2015; Sarker et al., 2005). Such research must consider beliefs (e.g., perceived enjoyment) and individual characteristics (e.g., self-efficacy, computer anxiety, and computer playfulness) currently used to predict BI and possible new beliefs and individual characteristics unique to the prediction of BE in these contexts (e.g., Thatcher & Perrewé, 2002; Thatcher et al., 2011; Thatcher, Zimmer, Gundlach, & McKnight, 2008; Venkatesh & Bala, 2008). Recently, researchers have proposed various dimensions of IT use (Burton-Jones & Straub, 2006; Jasperson et al., 2005). A fruitful future research direction will be to include BE and its determinants as predictors of these new dimensions of IT use. Furthermore, it will be important to study how IT use relates to performance at different levels of analysis, such as team performance (Fuller & Dennis, 2009), and contexts, such as e-government (Venkatesh, Chan, & Thong, 2012), e-commerce (Sia et al., 2009), health care (Hu, Hsu, Hu, & Chen, 2010; Venkatesh, Zhang, & Sykes, 2011), education (Booker et al., 2012), information science (Lee, Wei, & Hu, 2011), and consumer behavior (Kim et al., 2014).

Implications for practice

In addition to the contributions to theory, our research has important implications for practice. Our findings suggest that employees, particularly those with less experience, tend to weigh consideration of external factors that affect their use of IT for information-related needs. This is good news for managers because it affords them an opportunity to implement interventions that can improve the likelihood of such employees using the system. One way to accomplish this is by leveraging relevant external factors that influence behavior. Given that BI is influenced by internal factors,

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especially performance and effort expectancies, it is more likely to be influenced by design features rather than other managerial interventions. However, given that BE is largely influenced by external factors, it can be more readily influenced by managerial interventions. For example, the external focus associated with facilitating conditions and social influence indicates that developing training programs, creating support groups, and enabling employee participation in these activities is likely to have a positive impact on BE (Maruping & Magni, 2015). Also, various design characteristics can also enhance BE. In the context of group collaboration systems, past research has suggested that certain design characteristics can help teams improve productivity and performance (e.g., Zhang, Venkatesh, & Brown, 2011). Managers and system designers can potentially include these design characteristics to influence individuals' BE to use a system.

A second means of positively influencing BE is by leveraging the moderators: age, gender, experience, and voluntariness. These factors can be used to select target groups of initial adopters. By selecting those most likely to have favorable expectations, managers can create a positive implementation experience. For example, Venkatesh et al. (2003) found that effort expectancy would be a strong predictor of BI for inexperienced older women whereas performance expectancy would be a strong predictor of BI for young men. The results here are consistent with those findings. In addition, our results demonstrate that for inexperienced older women, social influence is a strong determinant of BE whereas for experienced older women, facilitating conditions is a strong determinant of BE. Taken together, these findings suggest that managers in mandatory-use settings will want to focus on fostering a strong, more collective buy-in to influence older women who have limited experience with the system. For mandatory or voluntary systems in which there are experienced women involved in the implementation, managers will want to ensure that the conditions facilitating system use are well established. These same findings can be used to design training interventions and select individuals who would benefit most from different types of training. Furthermore, the moderators can be used to identify users who are most likely to need support, thus giving managers an opportunity to ensure that adequate support is in place for those users.

Conclusion

We set out to identify and test the determinants of BE, which has recently been proposed as a stronger predictor of IT use than BI, and develop a holistic nomological net of IT adoption. To achieve this objective, we built on and extended UTAUT as well as recent research that introduces BE as a predictor of IT use (Venkatesh et al., 2006, 2008). We also identified two antecedents of BE and four moderators of the relationship between BE and its antecedents. The results provide strong support for our research model and hypotheses. Our research offers valuable insights on the sources and mechanisms of IT utilization in organizations. Considering the extent of underutilization of IT in organizations, our findings can be used by researchers and practitioners to understand and develop interventions to minimize such underutilization of IT.

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