Exploring the effects of direct experience on IT use: An organizational field study

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Abstract:
Empirical studies have investigated the effect of attitude and behavior on IT acceptance in organizations but yielded ambiguous results. Possibly they have not effectively accounted for the moderating effects of experience gained through direct interaction with the target technology. We examined the moderating effect of the length of direct experience on IT acceptance relationships and constructs. Using multi-group invariance analysis, we demonstrated that relationships between key IT acceptance constructs differed, depending on the user's experience. The incorporation of direct experience can lead to convergent results and contribute to further understanding of the process. We discuss some implications from the knowledge that IT use is a dynamic process and suggest that IT management must account for direct experience in their decision making.
Keywords: Direct experience, IT use, Technology acceptance model, Invariance analysis

Article:

1. Introduction

Companies invest millions of dollars in IT to gain leadership, maintain competitiveness, or comply with industry standards. Firms can accelerate technology diffusion by selecting the best available technology; however, end-users ultimately determine the effectiveness of the investment. Organizations generally take their internal users for granted and pay scant attention to their behavior after implementation and initial use.
The paucity of long-term/post-adoption research is not unique to IS. In fact, in general diffusion studies, a mere 0.2% focused on post-adoption behaviors even though it was traditionally known that adoption and use were distinct behaviors. Consequently, when IT managers have developed strategies to intervene with end-users, the decisions were often difficult because of lack of guidelines. It is apparent that post-adoption research was of great importance given the criticality of IT in sustaining business and its financial implication.

It is challenging to understand end-user behavior patterns and to manage continued use [3]. To explain IT adoption and usage, the TAM was introduced about 20 years ago. Even in the existing longitudinal studies, the length of use and user experience are generally limited to a few months of adoption. Szajna [24] stated that "experience gained over time" can be a potentially critical component that has not been addressed.
The general applicability of TAM has not been established for long-term use. Therefore, we addressed the following questions: what factors affect IT users' use decision in the long-term, e.g., after two years or beyond? As experience increases, how do users' decision structures change? Our goal was to study continued long-term IT use with a focus on the role of direct experience.

This was achieved in a two-fold process. First, we focused on the concept of direct experience, exploring attitude and behavioral intention towards IT use and their effect on various levels of user experience. Second, we extended our model and applied it to various contexts.

2. Conceptual background

2.1. Direct experience in IT use

In the context of IT use, a person is either a non-user or a potential adopter before becoming a user of technology. In assessing perceptions, we measure how non-users perceive adopting the use of technology while we measure users' perceptions of the actual use. The determinants of adoption and use are not the same; obviously the non-user has no direct experience and the user does, though there is direct experience and non-direct/ salient experience involving work or experience with a similar technology. In our study, we focused on direct experience gained through the use of the target technology.

While the effect of experience can be studied as a direct influencing factor [15,19], some IT studies have examined the effect of experience through differences between experience and inexperienced users, sometimes called non-adopters. Taylor and Todd [25] found that several linkages were significantly different between users and non-users, including the effect of intention on behavior, perceived usefulness on intention, ease of use on attitude, perceived behavioral control on behavior, and perceived behavioral control on intention. Karahanna et al. [16] examined non-adopters and initial users of the Windows™ operating system and found different strengths between behavioral beliefs, attitude, and intention. They argued that the perceptions of non-adopters and users are fundamentally different; non-adopters assessed their opinions and attitude towards adopting a technology while the users expressed opinions about using it.

Gefen et al. [13] tested a modified TAM on two groups of e-commerce store customers: experienced and non-adopters (inexperienced). They found the effect of perceived usefulness to be different. Castañeda et al. [5] found that experience moderated the effect of perceived ease of use and usefulness on intention to revisit a website.

2.2. How to study direct experience

The important research question was whether and how users differed because of their direct experience. It was necessary to determine how to model direct experience in the use of IT. One approach was to segment experience into levels rather than examining it at one aggregated level. Aggregation could cause findings to be unstable [8]. When experience levels are grouped, results may be mixed and few generalizations possible. Thompson et al. [26] extended a model developed in earlier work based on Triandis' theory of behavior [27]. They examined the moderating effect of experience on the relationship between six antecedent variables (social factors, affect, complexity, job fit, long-term consequences, and facilitating conditions) and PC application use. The inexperienced group consisted of actual users and not non-adopters. The study indicated strong moderating effects of experience on the relationship between the five factors and use.

To segment experience, we employed length of use as a proxy, allowing multiple levels of experience to be investigated. We examine three levels, long-, mid-, and short-term.

2.3. Long-term context of IT use

It is important to study IT use in the long-term as both ROI and diffusion take time and also that users gain direct experience only over time. But, how long is long-term? Customarily, the useful life of an IT innovation is projected at between 5 and 10 years. But IT innovation operates for much longer. For our study, we wanted to go beyond five years, to match the life of IT innovation.

3. Research model and hypotheses

In developing our hypotheses and model, we evaluated TAM and other models to examine key relationships that may vary across levels of experience. As we hoped to explain inconsistencies in TAM, it was necessary that our model did not deviate significantly from it, incorporating only material from TRA (normative beliefs and subjective norms) [5]. The research model is shown in Fig. 1.

In the form of subjective norms, social influence was assumed to be a determinant of behavioral intention in TRA. TRA proposed that intention was the psychological process that mediated the influence of attitude on behavior [12]; thus, intention served as a good proxy for behavior.

3.1. Research hypotheses

We examined the moderating effects of direct experience on several relationships, between: perceived usefulness and attitude (PU-A), perceived ease of use and attitude (EOU-A), attitude and behavioral intention (A-BI), and subjective norms and behavioral intention (SN-BI). Direct experience has been found to significantly moderate attitude relationships and belief/attitude strengths in social psychology [11]. However, attitudes are not always predictive of behavior and could change with experience [17].

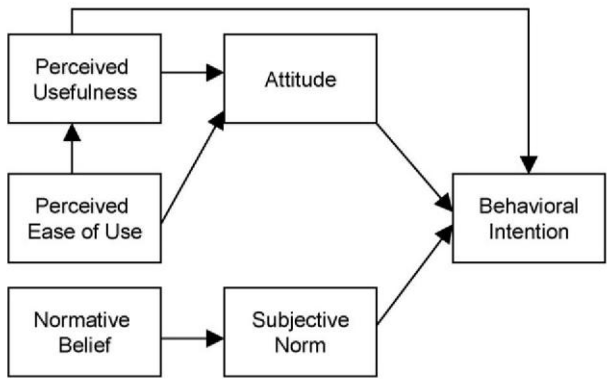

Fig. 1. Research model.

An attitude is the result of cognitive learning. Consequently, beliefs precede attitude. A key aspect is the information source from which beliefs are formed (direct or indirect experience). Indirect experience is gained when people receive information from other people, magazines, or observing others [22]. Beliefs induced by direct experience are, however, stronger and clearly defined and consistent with attitude.

In the context of IT acceptance, through continued use, more and better information is gained about the technology. Direct experience enhances accessibility of the attitude. Some studies have reported that perceived usefulness is a stronger determining factor of attitude for users [6]. This lead to our first hypothesis:

H1 The effect of perceived usefulness (PU) on attitude (A) will be stronger for IT users with higher level of experience than those with less experience.

While some IT studies found that ease of use was an insignificant determinant of attitude in the short-term [7], its effect on attitude had not been validated in the long-term. In fact, many speculated that the effect of ease of use was only temporary. However, according to social psychology, beliefs (including ease of use) become more consistent with attitude as users gain more experience. Therefore, we made our second hypothesis:

H2 The effect of perceived ease of use (EOU) on attitude (A) will be stronger for IT users with higher level of experience than those with less experience.

Social psychologists believe that attitude is central to behavior and recognize that good quality attitudes (strong attitudes) predict behavior well while less strong do not [9]. Strength of an attitude [20], affects the way that individuals behave consistently. As users gain experience, the direct interaction with an attitude strengthens it, and thus it becomes more predictive of their behavioral intention and behavior. Attitudinal qualities, such as clarity, confidence, and certainty gained through experience strengthen the attitude–behavior relationship [2]. In fact, Fazio and Zanna [10,11] found the attitude–behavioral relationship to be strongest in the high experience group, weak in the moderate group, and insignificant in the lowest group. Overall, there is consensus that direct experience moderates the attitude–behavior relationship [21]. Thus:

H3 The effect of attitude (A) on behavioral intention (BI) will be stronger for IT users with higher level of experience than those with less experience.

Subjective norms have been found a significant factor in determining attitude in some studies [23] while not in others [18]. Many studies have simply excluded the subjective norms construct. We believed it was important to recognize the conditions under which subjective norms were predictive of behavior. Users without experience are more susceptible to their influence but as users gain experience their behavior will be more internally determined by their attitude and beliefs. Some findings support the notion that as direct experience increases, the link between subjective norms and behavior weaken. Recognizing this, we postulated:

H4 The effect of subjective norms (SN) on behavioral intention (BI) will be weaker for IT users with higher level of experience than those with less experience.

Direct experience should strengthen beliefs. This leads to hypotheses that considered the moderating effects of direct experience on IT users' beliefs and attitude:

H5 The strength of perceived usefulness (PU) will be higher for IT users with higher level of experience than those with less experience.

H6 The strength of perceived ease of use (EOU) will be higher for IT users with higher level of experience than those with less experience.

H7 The strength of attitude (A) will be higher for IT users with higher level of experience than those with less experience.

4. Research methodology

4.1. Research setting

We segmented users into experience levels based on their length of use of a specific technology. In order to study users with long-term experience, the selected technology must have been available for a long time but it could not be so old that almost everyone had adopted it long ago. Furthermore, the measure of experience relies on the recall of the user. Therefore, we needed to select a technology that had been made widely available in the last 10 years. In advanced countries diffusion of IT in organizations started in 1960s. By contrast, IT diffusion is more recent in developing countries. China is one such country where major IT development started only in the late 1980s. It was relatively easy to find users with different levels of experience – so we chose China as our research target and Email was the target technology.

From the time email was introduced in China (late 1980s), sufficient time has elapsed to allow its widespread diffusion, allowing us to study users with various levels of experience. In a preliminary survey of Chinese companies, we found that email was one of the most accessible computer applications and its use was predominantly voluntary.

4.2. Operationalization of scales

We adopted existing scales as our measures: fully anchored 7- point Likert scales were used with end points "strongly disagree" (1) to "strongly agree" (7) for most items. The instrument was translated into Chinese and back-translated into English to ensure consistency. The wording was refined in a pretest by four native Chinese speakers including experienced and new users, thereby reinforcing face validity. The instrument was further validated through a pilot test. The resulting instrument (Appendix A), containing 22 items, was consistent with recommended short scales.

4.3. Data collection procedures

A field survey was employed. A total of 100 well- established companies in metropolitan areas of China were contacted by phone. Thirty agreed to participate. To ensure prompt collection and high response rate, we physically visited most companies. In total, 900 employees were asked to participate. The questionnaires were administered with both oral and written instructions. Because some employees had not adopted email, two survey forms were used, one for non-users and one for users, because we wished to word the questionnaire for each type of respondent. In addition, we needed to track the number of non-users to use in segmenting experience levels. Because our focus was on IT use, the non-users were not included in our study. Users were asked to recall the month and year when they first adopted email. This method has been used in many IS studies [14]. We also collected demographic data about the participant (age, gender, education, and position).

5. Data analysis

Of the 900 questionnaires distributed, 757 were returned and found useful, representing an 84% response rate. Therefore, non-response bias was not an issue [1]. There were 533 users and 224 non-users. Demographics of respondents are shown in Table 1.

5.1. Data subsets

The sample was segmented into three levels of experience. We adopted the innovation diffusion classification framework to develop this. It divided users into groups based on length of use and provided a more natural division than equal or randomly selected intervals. The framework separated users into innovator, early adopter, early majority, and late majority. Table 2 shows the percentage of each adopter category in this framework. Our sample has 70.4% users and 29.6% delayed adopters. According to innovation diffusion theory, laggards accounted for 16%. If our sample was representative, the potential adopter portion (29.6%) would consist of laggards (16%) and a part of the late majority (13.6%). In general, the late majority accounted for 34%, therefore, 13.6% of them were potential adopters and the remaining 20.4% were those who had adopted email. This distribution was then used to divide the 533 users into appropriate groups.

Table 1
Sample demographics

Variables	Sample composition	Percentage (%)
Age	18–22	7.1
	23–28	41.1
	29–34	23.2
	35–44	16.6
	45–55	8.4
	55+	1.6
	Not reported	2.1
Gender	Men	63.7
	Women	30.3
	Not reported	6.0
Highest educational level attained	Junior high	1.3
	High school	9.5
	Associate degree	22.7
	College degree	44.1
	Master's	12.2
	Doctorate	8.4
	Not reported	1.9
Organizational level represented	Executive	1.6
	Management	29.8
	Professional	35.4
	Technical/clerk	21.4
	Researcher	9.9
	Not reported	1.8

Table 2
Innovation diffusion theory adopter distribution

Type	%
Innovator	2.5
Early adopter	13.5
Early majority	34.0
Late majority	34.0
Laggards	16.0

Table 3 shows the approximate sizes of the user groups based on the framework. We named the groups: extra long-term, long-term, mid-term, short-term, and zero experience.

Table 3
Sample segmentation based on experience

Sample segment (by experience)	Innovation diffusion theory framework	Sample (%)	Relative (%)	Sample size (*N*)	Date of first use (mm/yy)	Length of experience (years)
Levels of experience	User	70.4		533		
Extra long-term	Innovator	2.5	3.0	19	01/87–11/92	
Long-term	Early adopter	13.5	19.0	101	12/92–03/97	6.5
Mid-term	Early majority	34.0	48.0	258	04/97–11/98	3
Short-term	Late majority	20.4	29.0	155	12/98–06/00	1.5
Zero experience	Potential Adopter	29.6		224		0
Non-adopter	Late majority	13.6				
	Laggards	16				

As the sample size of the extra long-term group was quite small (N=19) and not suitable for most statistical tests, this group was excluded from further analysis. In addition, because our focus was on post-adoption, we did not include the zero experience users (non-adopters) further. The three remaining groups were then called: long-term, mid-term, and short-term.

Table 4
Reliability measures by sample segments

Construct	Long-term	Mid-term	Short-term
	Cronbach's α		
Perceived usefulness	.91	.89	.83
Perceived ease of use	.80	.77	.77
Normative believes	.90	.93	.90
Attitude	.89	.90	.85
Subjective norms	.94	.91	.93
Behavioral intention	.91	.83	.83
	Composite factor reliability (CFR)		
Perceived usefulness	.85	.87	.83
Perceived ease of use	.83	.84	.86
Normative believes	.87	.89	.83
Attitude	.90	.90	.87
Subjective norms	.94	.91	.93
Behavioral intention	.91	.84	.85
	Average variance extracted (AVE)		
Perceived usefulness	.53	.57	.50
Perceived ease of use	.55	.57	.56
Normative believes	.63	.67	.56
Attitude	.69	.69	.63
Subjective norms	.89	.84	.87
Behavioral intention	.78	.63	.67

5.2. Instrument quality and model fit

Table 4 shows the reliability measures. Confirmatory factor analysis was conducted for each group to establish convergent and discriminant validity. All factor loadings were significant. Additionally, the risk of multicollinearity was assessed. Each indicator was regressed against all other indicators within the same construct. All variance inflation factors were less than 10 indicating that multicollinearity was not significant. With validity and reliability established, the models were assessed with structural equation modeling techniques using LISREL 8.30. Missing data were treated with the listwise procedure. Multiple measures of fit were used. As shown in Table 5, the measurement model statistics showed good fit. The structural model fit indices (Table 6) indicated good model fit of all three datasets. Fig. 2 shows the estimated standardized path coefficients and their significance level for the three groups and the variance explained for attitude and behavioral intention.

5.3. Hypothesis testing

For testing H1, H2, H3, and H4, we employed multi-group invariance analysis to assess the equality of regression coefficients. Thus, for each hypothesis the statistical difference in the parameter across experience levels was assessed using three pairwise comparisons (e.g., for Hypothesis 1: in H1a, long-term and mid-term groups were compared, etc.). The hypotheses and the series of multi-group analyses are shown in the first two columns of Table 7. The multi-group invariance analysis investigated parameter difference by comparing a baseline model to a subsequent model in which all parameters were reestimated except for the regression coefficients of interest. A baseline model was compared with a subsequent model for χ^2 difference. Based on Bollen's [4] recommendation, the baseline model (Run 1) is the least restrictive. In the subsequent model (Run

2), the regression coefficients of interest were restricted to be the same across groups while allowing the remaining coefficients to be reestimated.

Table 5
Measurement model fit statistics

Fit index	Long-term experience	Mid-term experience	Short-term experience	Recommended cutoff
Normed χ^2 (χ^2/d.f.)	1.71	1.99	1.56	Below 3
CFI	.95	.96	.96	Above .90
NFI	.90	.93	.90	Above .90
NNFI	.94	.95	.95	Above .90
IFI	.95	.96	.96	Above .90
RMSEA	.085	.065	.06	Below .08

Table 6
Structural model fit statistics

Fit index	Long-term experience	Mid-term experience	Short-term experience	Recommended cutoff
Normed χ^2 (χ^2/d.f.)	2.00	2.41	1.83	Below 3
CFI	.94	.95	.95	Above .90
NFI	.89	.92	.89	Above .90
NNFI	.94	.95	.94	Above .90
IFI	.95	.95	.95	Above .90
RMSEA	.091	.069	.066	Below .08

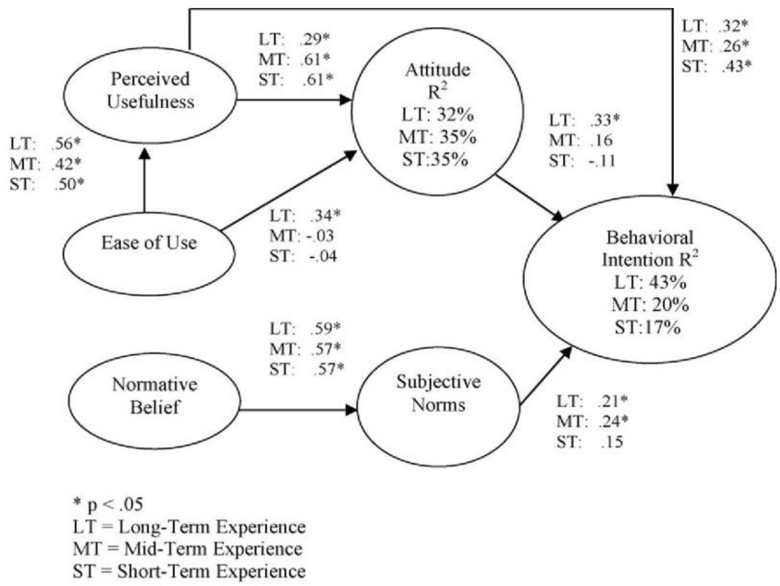

Fig. 2. Structural model estimates by data segments.

Table 7
Multi-group comparisons and hypothesis testing results

Hypothesis	Sample/experience group	Hypothesis support
H1	H1a: long-term–mid-term	SOD*
	H1b: long-term–short-term	Marginal
	H1c: mid-term–short-term	Not supported
H2	H2a: long-term–mid-term	Supported
	H2b: long-term–short-term	Marginal
	H2c: mid-term–short-term	Not Supported
H3	H3a: long-term–mid-term	Not Supported
	H3b: long-term–short-term	Supported
	H3c: mid-term–short-term	Supported
H4	H4a: long-term–mid-term	Not Supported
	H4b: Long-Term – Short-Term	Not Supported
	H4c: Mid-Term – Short-Term	Not Supported

Notes: *$p < .05$; SOD, significant but opposite direction; Marginal, supported at .10 level.

Table 8
Multi-group analysis for hypotheses

Model	Run number	Description	χ^2	d.f.	$\Delta\chi^2$ from Run 1	*p*-Value
Hypothesis 1						
1a	1	Non-restrictive	767	197	0	
1a	2	$\gamma_{A,PU}$ restricted	782	198	14.56	.0001
1b	1	Non-restrictive	560	197	0	
1b	2	$\gamma_{A,PU}$ restricted	563	198	2.88	.0897
1c	1	Non-restrictive	317	197	0	
1c	2	$\gamma_{A,PU}$ restricted	317	198	.29	.5902
Hypothesis 2						
2a	1	Non-restrictive	767	197	0	
2a	2	$\gamma_{A,EOU}$ restricted	774	198	6.7	.0096
2b	1	Non-restrictive	560	197	0	
2b	2	$\gamma_{A,EOU}$ restricted	563	198	3.15	.0759
2c	1	Non-restrictive	317	197	0	
2c	2	$\gamma_{A,EOU}$ restricted	317	198	.16	.6892
Hypothesis 3						
3a	1	Non-restrictive	241	59	0	
3a	2	$\gamma_{BI,A}$ restricted	242	60	.92	.3375
3b	1	Non-restrictive	114	59	0	
3b	2	$\gamma_{BI,A}$ restricted	137	60	23.37	.0000
3c	1	Non-restrictive	150	59	0	
3c	2	$\gamma_{BI,A}$ restricted	156	60	5.9	.0151
Hypothesis 4						
4a	1	Non-restrictive	241	59	0	
4a	2	$\gamma_{BI,SN}$ restricted	241	60	.01	.9203
4b	1	Non-restrictive	114	59	0	
4b	2	$\gamma_{BI,SN}$ restricted	114	60	.05	.8231
4c	1	Non-restrictive	150	59	0	
4c	2	$\gamma_{BI,SN}$ restricted	150	60	.05	.8231

Therefore, the χ^2 difference between the two runs became the coefficient of interest. A significant χ^2 difference indicated that the specific path coefficient was different between the groups being compared. The multi-group analysis, shown in Table 8, reported the χ^2, degrees of freedom, and the change in χ^2 along with its significance level. Table 9 summarizes the differences across experience levels. Overall, we found partial support for H1, H2, and H3 and no support for H4. H5, H6, and H7 discuss the strengths of constructs across experience levels. The ANOVA results, shown in Table 10, corroborated that beliefs, attitude, and intentions strengthened with experience. Thus H5, H6, and H7 were supported. Beliefs (perceived usefulness and ease of use) and attitude all strengthened as user experience level increased.

6. Discussion

We enriched our understanding of IT user behavior beyond adoption and short-term use by studying users as multiple groups based on their experience in an organizational setting.

Table 9
Multi-group analysis results tabulated by experience levels

Structural path	Hypothesis support Experience-level comparison pair		
	Long-term vs. mid-term	Long-term vs. short-term	Mid-term vs. short-term
PU → A	SOD	Marginal	–
EOU → A	Supported	Marginal	–
A → BI	–	Supported	Supported
SN → BI	–	–	–
Total number ($p < .05$)	1	1	1

Notes: SOD, significant but opposite direction; Marginal, supported at .10 level.

Table 10
ANOVA test across experience levels

Hypothesis	Construct	Long-term experience	Mid-term experience	Short-term experience	ANOVA results	Hypothesis support
H5	PU	6.02[a] (.78[b])	5.70 (.87)	5.56 (.74)	21.94[c] (p = .00)	Yes
H6	PEOU	5.89 (.69)	5.80 (.75)	5.67 (.72)	30.84 (p = .00)	Yes
H7	A	5.95 (.77)	5.55 (.81)	5.37 (.79)	36.89 (p = .00)	Yes

Notes: PU, perceived usefulness; PEOU; perceived ease of use; A, attitude.
[a] Mean.
[b] Standard deviation.
[c] *F*-value.

6. 1. Experience and determinants of attitude

Perceived usefulness was significant for users at all experience levels. In fact, it was the only factor that was significant in most prior studies. Thus, perceived usefulness is a good predictor of attitude for all users. When the strength of the effect of perceived usefulness on attitude was compared across time, it was found to differ significantly between long-term and mid-term users and marginally between long-term and short-term users. The effect of usefulness in the long-term, although significant, seemed to diminish after mid-term experience. For majority of users, once the innovation was adopted, the users tended to discover more functionalities (or lack thereof) and their attitudes were affected accordingly. Long-term IT users had the most direct experience, their attitudes were formed and they were less likely to be affected by changes in usefulness. Possibly habit came into play at this stage.

While the effect of perceived usefulness on attitude was significant for users at all levels, perceived ease of use was significant only for long-term users. Apparently ease of use was not a compelling factor in shaping attitude for mid- and short-term users but perceived usefulness was. The long-term IT users formed attitude about the technology not only because of usefulness but also because of ease of use. These findings have provided an explanation of the unstable effects seen in some studies where perceived ease of use was not significant; maybe merging all user groups diluted the effect of this variable.

6.2. Experience and determinants of behavioral intention
In our study, the effect of attitude on behavioral intention was significant for only long-term users. The attitude–behavior relationship did not exist in the mid- and short-term users. While we did not find a clear moderating effect of direct experience on the SN–BI relationship, we found that it was significant for long-and mid-term users but not for short-term ones.

Overall, both attitude and norms tend to be consistent with behavior as a person continues to use IT. As IT users become more experienced, their perceived internal influences (such as attitude) and external influences (norms) are more consistent with their technology use.

6.3. Applicability of the research model across experience levels
Overall, our fit indices were adequate. The predictive power of the model in terms of explained variance varies across experience levels: R_A^2 = 0.32 and R_{BI}^2 = 0.37 for long-term users, R_A^2 = 0.35 and R_{BI}^2 = 0.20 for mid-term users, and R_A^2 = 0.35 and R_{BI}^2 = 0.17 for short-term users. Although the sources differed, the model was able to explain similar amount of variance in attitude across experience levels. The model predicts long-term users' behavioral intention best.

Prior research showed much variability in the model predictive ability. We contend that the inconsistencies were due to their treatment of direct experience.

6.4. External validity and limitations
The study was conducted in China. This allowed us to examine a recent innovation and categorize experience with relative ease. One can, however, make the argument that users in different cultures may behave and act differently. Nevertheless, we believe that our results would apply in similar contexts, and to a limited degree in other contexts and cultures.

Another limitation includes that generally associated with survey methodology and the cross-sectional nature of data. Also, while we used an elaborate method for classifying the three groups based on experience, there may be other ways of making the classification.

7. Implications and conclusions
Through hypotheses testing, we were able to demonstrate that long-, mid-, and short-term users were significantly different along some key dimensions. We found that long-term use was well predicted, and as experience increased, the causal structure changed. Contrary to conventional beliefs, subjective norms played a significant role in determining behavioral intention in the mid-and long-term.

7.1. Implications for practice
A view into the behaviors of users with varying levels of experience can help IT managers in a number of ways. First, our results have a direct bearing on IT diffusion management and could assist IT managers in making sound decisions. Our results could help improve IT diffusion speed, thus innovation speed, which is critical to organizational competitiveness. Currently, the effectiveness of training programs has been minimal and the effectiveness of such programs seldom evaluated. As effective marketing strategies involve long-term education and interaction with consumers, managers need to develop long-term training and on-going support programs. Periodic and long-term programs would enhance positive beliefs and attitudes, increasing the likelihood that users would use IT on a sustained basis.

Our results showed that more experienced IT users have more positive perceptions, attitudes, and behavioral intentions. Consequently, they will make more significant use of technology. This has significant implications: managers should orient their interaction/training programs to encourage early adoption and faster rate of adoption in order to maximize ROI.

Ultimately, the diffusion process involves reducing uncertainties. Our study shows organizational managers how IT acceptance depends on the level of user experience. Targeted effort can effectively enhance the diffusion process and help achieve better acceptance of promising innovations.

Appendix A. List of items used in the final analysis

	Item	Description
Perceived usefulness (PU)		
1	PU1	Using E-Mail helps me to accomplish tasks more quickly
2	PU2	Using E-Mail improves the quality of my work
3	PU3	Using E-Mail enhances my effectiveness on the job
4	PU4	Using E-Mail makes my job easier
5	PU5	I find E-Mail useful in my job
Perceived ease of use (EOU)		
6	EOU1	Learning to use E-Mail was easy for me
7	EOU2	E-Mail is easy to use
8	EOU3	My interaction with E-Mail is clear and understandable
9	EOU4	It is easy for me to become skillful at using E-Mail
Normative beliefs (NB)		
10	NB1	Top management thinks I should use E-Mail
11	NB2	Peers think I should use E-Mail
12	NB3	Friends think I should use E-Mail
13	NB4	Computer Specialists in the company think I should use E-Mail
Attitude (A)		
14	A1	Using E-Mail on my job is extremely good ... extremely bad
15	A2	Using E-Mail on my job is extremely harmful ... extremely beneficial
16	A3	Using E-Mail on my job is useless .... Useful
17	A4	Using E-Mail on my job is worthless ... valuable
Subjective norms (SN)		
18	SN1	Most people who are important to me think I should use E-Mail
19	SN2	Most people who influence my behavior think I should use E-Mail
Behavioral intention (BI)		
20	BI1	I intend to continue using E-Mail
21	BI2	Assuming I had access to E-Mail, I intend to use it
22	BI3	Given that I had access to E-Mail, I predict that I would use it

References

[1] E.R. Babbie, The Practice of Social Research, California, Wadsworth, Belmont, 1998.

[2] P.M. Bentler, G. Speckart, Models of attitude–behavior relations, Psychological Review 86 (5) (1979) 452–464.

[3] A. Bhattacherjee, Understanding information systems continuance: an expectation-confirmation model, MIS Quarterly 25 (3) (2001) 351–370.

[4] K.A. Bollen, Structural Equations with Latent Variables, Wiley, New York, 1989.

[5] J.A. Castañeda, F. Muñoz-Leiva, T. Luque, Web acceptance model (WAM): moderating effects of user experience*, Information & Management 44 (4) (2007) 384.

[6] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Quarterly 13 (3) (1989) 319–339.
[7] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, User acceptance of computer technology: a comparison of two theoretical models, Management Science 35 (8) (1989) 982–1003.
[8] G.W. Downs Jr., L.B. Mohr, Conceptual issues in the study of innovation, Administrative Science Quarterly 21 (4)(1976) 700–714.
[9] A.H. Eagly, S. Chaiken, The Psychology of Attitudes, Harcourt Brace Jovanovich College Publishers, Fort Worth, 1993.
[10] R.H. Fazio, M.P. Zanna, Attitudinal qualities relating to the strength of the attitude–behavior relationship, Journal of Experimental Social Psychology 14 (1978)398–408.
[11] R.H. Fazio, M.P. Zanna, Direct experience and attitude–behavior consistency, in: L. Berkowitz (Ed.), Advances in Experimental Social Psychology, vol. 14, Academic Press, New York, 1981, pp. 161–202.
[12] M. Fishbein, I. Ajzen, Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research, Addison-Wesley, Reading, MA, 1975.
[13] D. Gefen, E. Karahanna, D.W. Straub, S. Page, Inexperience and experience with online stores: the importance of TAM and trust, IEEE Transactions on Engineering Management 50 (3) (2003) 307–321.
[14] V. Grover, K. Fiedler, J. Teng, Empirical evidence on Swanson's tri-core model of information systems innovation, Information Systems Research 8 (3) (1997) 273.
[15] I. Ha, Y. Yoon, M. Choi, Determinants of adoption of mobile games under mobile broadband wireless access environment, Information & Management 44 (3) (2007) 276.
[16] E. Karahanna, D.W. Straub, N.L. Chervany, Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs, MIS Quarterly 23 (2) (1999) 183–213.
[17] C.G. Lord, R.M. Paulson, T.L. Sia, J.C. Thomas, M.R. Lepper, Houses built on sand: effects of exemplar stability on susceptibility to attitude change, Journal of Personality And Social Psychology 87 (6) (2004) 733–749.
[18] K. Mathieson, Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior, Information Systems Research 2 (3) (1991)173–191.
[19] V. Mellarkod, R. Appan, D.R. Jones, K. Sherif, A multi-level analysis of factors affecting software developers' intention to reuse software assets: an empirical investigation, Information & Management 44 (7) (2007) 613.
[20] J.M. Olson, M.P. Zanna, Attitudes and attitude change, Annual Review of Psychology 44 (1) (1993) 117–156.
[21] D. Raden, Strength-related attitude dimensions, Social Psychology Quarterly 48 (a) (1985) 312–330.
[22] D.T. Regan, R.H. Fazio, On the consistency between attitudes and behavior: look to the method of attitude formation, Journal of Experimental Social Psychology 13 (1977)28–45.
[23] D.C. Robertson, Social determinants of information system use, Journal of Management Information Systems 5 (4) (1989) 55–71.
[24] B. Szajna, Empirical evaluation of the revised technology acceptance model, Management Science 42 (1) (1996) 85–92.
[25] S. Taylor, P. Todd, Assessing IT usage: the role of prior experience, MIS Quarterly 19 (4) (1995) 561–570.
[26] R.L. Thompson, C.A. Higgins, J.M. Howell, Influence of experience on personal computer utilization: testing a conceptual model, Journal of Management Information Systems 11 (1) (1994) 167.
[27] H.C. Triandis, Values, attitudes and interpersonal behavior, in: H.E. Howe (Ed.), Nebraska Symposium Motivation, 1979, Beliefs, Attitudes and Values, University of Nebraska Press, Lincoln, 1980, pp. 195–259.