MIS Quarterly

RESEARCH ARTICLE

UNDERSTANDING CHANGES IN BELIEF AND ATTITUDE TOWARD INFORMATION TECHNOLOGY USAGE: A THEORETICAL MODEL AND LONGITUDINAL TEST[1]

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Abstract

User beliefs and attitudes are key perceptions driving information technology usage. These perceptions, however, may change with time as users gain first-hand experience with IT usage, which, in turn, may change their subsequent IT usage behavior. This paper elaborates how users' beliefs and attitudes change during the course of their IT usage, defines emergent constructs driving such change, and proposes a temporal model of belief and attitude change by drawing on expectation-disconfirmation theory and the extant IT usage literature. Student data from two longitudinal studies in end-user computing (computer-based training system usage) and system development (rapid application development software usage) contexts provided empirical support for the hypothesized model, demonstrated its generalizability across technologies and usage contexts, and allowed us to probe context-specific differences. Content analysis of qualitative data validated some of our quantitative results. We report that emergent factors such as disconfirmation and satisfaction are critical to understanding changes in IT users' beliefs and attitudes and recommend that they be included in future process models of IT usage.

Keywords: Information systems, usage, acceptance, attitude, belief, perceived usefulness, expectation disconfirmation theory

Introduction

Change is an inevitable and inalienable part of human life. We continually adjust, revise, and

[1]Ritu Agarwal was the accepting senior editor for this paper.

even reverse our personal beliefs, our opinions of others, our views of social institutions, and our own behaviors as we learn more about our social environments and our own behaviors. Likewise, our beliefs, attitude, intention, and usage of information technology (IT) innovations also change over time as we experience IT usage first-hand and learn from such use. In 1990, Melone (1990) stated, "For the most part, the IS literature is silent on how users form initial attitudes about technologies and how these attitudes are *modified over time*" (emphasis added). Since then, although a growing body of IT usage research has examined formation of initial beliefs and attitudes, to date, very little research has been directed at explicating why and how beliefs and attitudes change over time. Explaining *temporal changes* in users' beliefs and attitude toward IT usage is the goal of this study.

We focus on user beliefs (specifically, perceived usefulness) and attitude because prior studies of IT usage, predominantly based on the technology acceptance model (TAM) and similar models, have established these perceptions as the key determinants of both initial IT usage (acceptance) and long-term usage (continuance) intention and behavior (Bhattacherjee 2001; Davis et al. 1989). Any change in beliefs or attitudes will likely have a corresponding impact on, and may even reverse, users' continuance intention and behavior. Such reversal in one's IT usage behavior from initial acceptance to later discontinuance, which Bhattacherjee (2001) termed the "acceptance-discontinuance anomaly," may undermine organizational efforts directed at exploiting the full potential of IT as a means of enhancing employee productivity, efficiency, and effectiveness in the workplace.

Prior research (e.g., Sjazna and Scamell 1993; Venkatesh and Morris 2000) provides preliminary empirical evidence that user beliefs and attitudes do change over time, although to date no study has examined or validated potential reasons for such change. Our study builds on these studies by theorizing and empirically validating the causative drivers and emergent mechanisms driving temporal changes in user beliefs and attitude toward IT usage. In doing so, it extends the traditional static models of IT usage by bringing in a dynamic perspective, explicates emergent constructs that can explain temporal patterns in IT usage, and also resolves some of the prior empirical inconsistencies in the referent literature.

The three research questions of interest to this study are:

(1) Do IT users' beliefs and attitude toward IT usage change over time as they experience IT usage first-hand?
(2) What *emergent* factors, if any, drive this change and why?
(3) To what extent are these effects generalizable across technology and IT usage contexts?

To address these questions, we draw upon expectation-disconfirmation theory (EDT) (Oliver 1980) and prior TAM research to propose a two-stage model of belief and attitude change. Empirical data collected using student subjects employing longitudinal studies of computer-based tutorial (CBT) and rapid application development (RAD) system usage validated the hypothesized model across two different technologies and usage contexts. Observed differences between the two studies allowed us to probe into and examine the implications of specific contextual differences. Qualitative analysis of respondents' comments from the CBT study helped triangulate and validate some of our quantitative results.

The rest of the paper proceeds as follows. The next section integrates EDT with the IT usage literature to build a theoretical model of belief and attitude change. The third section describes the two empirical studies that test the proposed model. The fourth section describes instrument construction and validation. The fifth section empirically tests the hypothesized model across the CBT and RAD studies, performs *post hoc* analysis, and examines qualitative data from the CBT study. The final section discusses the theoretical and practical contributions of the study's findings and presents avenues for future research.

Theory and Research Model

Expectation Disconfirmation Theory

Expectation-disconfirmation theory (EDT) (Oliver 1980), an extension of cognitive dissonance theory (CDT) in the social psychology literature, has been used by researchers to understand consumer satisfaction, repurchase intentions, and complaining behaviors in contexts ranging from automobile repurchase (e.g., Oliver 1993), camcorder repurchase (e.g., Spreng et al. 1996), restaurant services (e.g., Swan and Trawick 1981), business professional services (e.g., Patterson et al. 1997), and, most recently, IT usage (e.g., Bhattacherjee 2001). CDT was formulated by Festinger (1957) to explain how discrepancies (dissonance) between one's cognition and reality change the person's subsequent cognition and/or behavior. Cognition, in this context, refers to one's beliefs, affect, opinion, values, and knowledge about one's environment, while behavior refers to actions initiated in response to this cognition and/or personal evaluation of that behavior (Festinger 1957).

In IT usage contexts, CDT suggests that users' pre-usage cognitions (e.g., beliefs, attitude) are generally based on second-hand information, such as vendor claims or industry reports, communicated via interpersonal or mass media channels. Such communicated information may be exaggerated (by vendors) or unrealistic, resulting in cognitions that are less reliable or stable. Over time, as users gain first-hand experience with IT usage, they evaluate the extent to which their initial cognition is consonant or dissonant with actual experience, and revise their cognition and/or behavior to achieve greater consonance. Cognitions are generally more easily changed than behaviors, especially under circumstances where users lack complete volition over their behavior (e.g., at the workplace). Over time, user cognitions reach a steady-state equilibrium, as they become more realistic and entrenched in observed behaviors.

EDT expands on CDT to depict a process model of individual behavior whereby users form an initial pre-usage expectation (belief) about a product, experience its usage over time, and then form post-usage perceptions of the product. The dissonance between users' original expectations and observed performance is captured in the disconfirmation construct. Disconfirmation may be positive or negative depending on whether the observed performance is above or below initial expectations, and is viewed as a deviation from the initial expectation (as the baseline or reference level). Disconfirmation and initial expectation jointly determine user satisfaction or dissatisfaction with the product, which then determines continued product usage or non-usage. Disconfirmation (a belief) and satisfaction (an affect) are, therefore, the two emergent constructs in EDT hypothesized to change subsequent user behavior.

The relationship between expectations and disconfirmation (and hence satisfaction) is somewhat complex (Yi 1990). Most researchers expect these two constructs to be negatively related, since high expectations are more likely to be negatively disconfirmed and low expectations are positively disconfirmed (Yi 1990). Empirically, however, this effect appears to be mixed (e.g., Bearden and Teel 1983; Churchill and Suprenant 1982). Some contend that this ambiguity is an artifact of multiple operationalizations of the disconfirmation construct, measured alternatively as the difference score between expected and realized levels of the overall product or of predefined product attributes, and perceived *post hoc* difference between expectations and performance (Yi 1990). Spreng et al. (1996) suggested that one's disconfirmation should be evaluated with respect to her *desired* product attributes, rather than *expected* product attributes. Patterson et al. (1997) observed that product expectation is an inadequate construct and should be expanded to include *fairness* of expectations as well.

Although most empirical EDT research directly linked disconfirmation and/or satisfaction to subsequent user intention (e.g., Bhattacherjee 2001; Patterson et al. 1997; Spreng et al. 1996), Oliver

(1980), in his original conceptualization of EDT, described a mediated model where the impact of disconfirmation and satisfaction on later intention was mediated by later belief and attitude. In other words, EDT can be viewed as a two-stage model where later-stage expectation (belief) and attitude at time t_2 is caused by initial-stage expectation and attitude at time t_1 and also disconfirmation and satisfaction realized at time t_2. While disconfirmation and satisfaction capture the cognitive effects of the interim usage experience, initial-stage expectation and attitude may also have a residual effect on the formation of later-stage expectation and attitude by serving as the baseline against which disconfirmation and satisfaction are assessed.

Oliver's (1980) two-stage EDT model was empirically validated in the marketing literature by Bearden and Teel (1983), using a two-period longitudinal study, and by Boulding et al. (1993) and Olson and Dover (1979), using three-period studies.[2] These three-period studies, employing data from one pre-usage and two post-usage time periods, demonstrate that the effect of disconfirmation on later-stage expectation or intention tend to stabilize or "wear off" over time as expectation stabilizes and becomes more consonant with actual experience.

CDT/EDT, as a theoretical referent, is just beginning to gain prominence in the IS usage literature. Szajna and Scamell (1993) designed a laboratory experiment where user expectations were manipulated to be unrealistically high, unrealistically low, or realistic, and found that (1) user expectations change over time as unrealistically high or low expectations tend to wear off over time and regress toward realistic levels, and (2) user satisfaction was significantly different among the realistic, unrealistically high, and unrealistically low groups, although there were no substantive difference in users' decision performance. The authors explained the observed expectation change in terms of cognitive dissonance, but did not operationalize or measure dissonance, and were therefore unable to validate the causative mechanism driving this change. However, they recommended that future studies should investigate the dissonance (disconfirmation) construct in order to better explicate why and how expectations change across time.

In a cross-sectional field survey of online banking, Bhattacherjee (2001) demonstrated that EDT-based constructs such as disconfirmation and satisfaction can successfully explain the continuance intention among online banking users. However, this study did not measure later-stage beliefs and attitudes, which may be immediate antecedents of continuance intention. Although this study suggested that these emergent constructs may explain temporal reversal in IT usage behavior from acceptance to discontinuance, it did not empirically examine such temporal change. In a two-period laboratory experiment, McKinney et al. (2002) used EDT to explain student subjects' satisfaction with online retailers, separately focusing on users' disconfirmation with an online retailing site and with the quality of information presented on that site.

While the above studies established the validity of CDT or EDT in IT usage contexts (McKinney et al. 2002), provided preliminary evidence of temporal changes in user beliefs (Szajna and Scammell 1993), and noted that continuance intention is impacted by emergent constructs such as disconfirmation and satisfaction (Bhattacherjee 2001), no study has yet examined the process by which user beliefs (expectations) or attitude regarding IT usage change over time from the pre-usage stage to usage stage, or the role of emergent constructs in driving that change. Our study addresses this gap in the literature by proposing an EDT-based process model of belief and attitude change.

[2]We distinguish a *stage* from a *period* as follows. A stage refers to a temporal phase in a theoretical process model that is unique and distinct in terms of its causative drivers. For instance, IT acceptance and IT continuance represent two stages of IT usage, but TAM is a single-stage model since it deals only with IT acceptance. In contrast, a period refers to a time span between two temporally distinct points in time (e.g., t_1–t_2) in a longitudinal empirical study. For instance, capturing TAM constructs at two distinct times results in a two-period (but still single-stage) study.

Prior Research on IT Usage

A vast body of research, based on technology acceptance model (TAM), theory of planned behavior (TPB), and related theories, has examined the effects of user beliefs and attitude on IT usage intention and behavior (e.g., Ajzen and Fishbein 1977; Davis et al. 1989; Taylor and Todd 1995b; Venkatesh and Davis 2000). This research demonstrates that perceived usefulness (the extent to which users believe that system usage will enhance their job performance) is the primary belief driving IT usage intention, whose effect on the dependent variable is partially mediated by attitude (personal affect toward IT usage). In other words, perceived usefulness and attitude are both important predictors of IT usage intention.

Recent longitudinal studies of IT usage suggest interesting temporal patterns in the causal associations predicted from TAM. Following a three-period study of technology use in the workplace, Venkatesh and Morris (2000) found that perceived usefulness has a strong persistent effect on user intention, ease of use has a smaller effect, and both effects are moderated by users' gender. However, since the goal of their study was to explore gender differences in technology usage patterns, the authors did not delve into the temporal drivers of these beliefs. In another study, Szajna (1996) found perceived usefulness to be a strong and consistent predictor of usage intentions across time, but found ease of use to have a declining effect, eventually becoming nonsignificant at a later point in time. This finding has prompted IS researchers to drop the ease of use construct, especially when studying later-stage usage or continuance. Among other longitudinal studies, Taylor and Todd (1995a) examined students' usage of a computer laboratory over a 12-week period and found that the strength of effects predicted by TAM was different for experienced compared to novice users, suggesting user experience as an important moderator. Venkatesh and Davis (2000) constructed a TAM2 model by adding experience, job relevance, image, and voluntariness constructs to TAM, and validated it using longitudinal data from four organizations in three time periods. Using a two-period survey of U.S. households, Venkatesh and Brown (2001) inferred that different sets of belief structures (attitudinal, normative, and control) explain family adoption versus non-adoption of personal computers.

Although the above longitudinal studies provided some preliminary evidence regarding temporal changes in TAM constructs such as perceived usefulness (e.g., Venkatesh and Morris 2000), they do not attempt to explain why or how these constructs change with time or the emergent factors driving such change. Further, by virtue of being single-stage models of IT usage, the above models cannot theoretically identify any such emergent factors. We attempt to fill this crucial gap in the IT usage literature by drawing on EDT to posit two emergent constructs driving belief and attitude change.

Research Model

We postulate a two-stage model of belief and attitude change, linking perceived usefulness and attitude in the pre-usage stage with those in the usage stage and positing disconfirmation and satisfaction as emergent constructs influencing post-usage usefulness and attitude (see Figure 1). Our choice of usefulness and attitude was motivated by their salience in the TAM literature as the predominant predictors of IT usage intention and their stable impact on the dependent variable over time (Davis et al. 1989). Continuance intention is also included to ground our model within the extant literature on IT usage, even though understanding intention is not the focus of this study. Although we excluded other IT-usage related beliefs such as ease of use, our analysis may be generalizable to those beliefs as well.

How do belief and attitude change from pre-usage stage to usage stage? EDT posits disconfirmation and satisfaction as the two emergent constructs driving such change (Oliver 1980). Disconfirmation is hypothesized to impact usefulness, since both constructs represent user beliefs regarding IT usage, while satisfaction is linked to

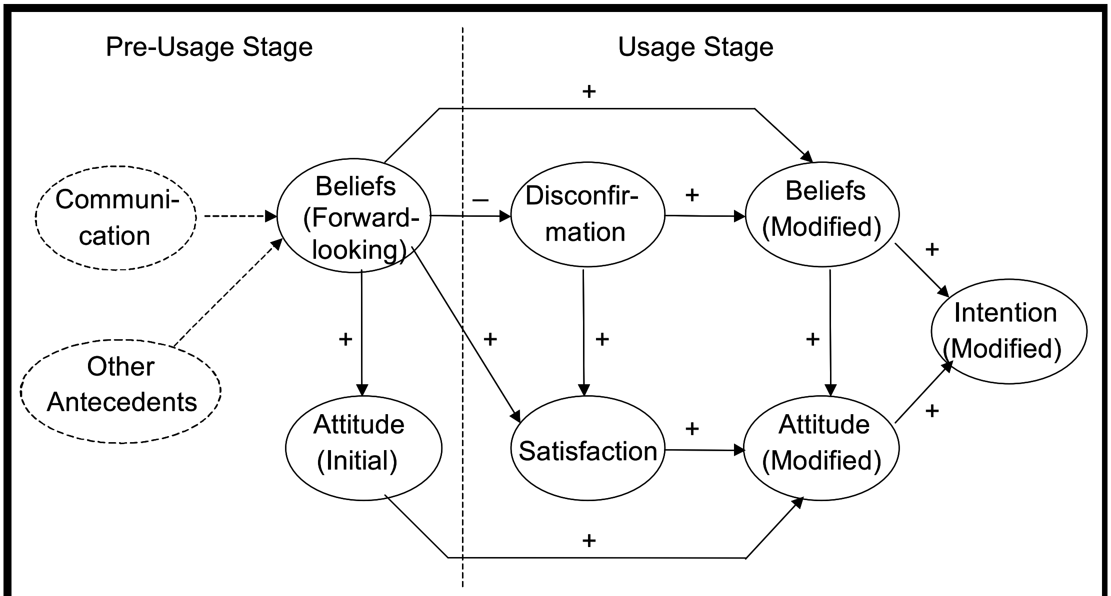

Figure 1. A Two-Stage Theoretical Model of Cognition Change

attitude, since these constructs represent user affect. Further, based on Oliver's (1980) partially mediated model, we propose pre-usage beliefs and attitude to have direct effects on usage-stage beliefs and attitude in addition to indirect effects via the disconfirmation and satisfaction constructs. Theoretical support for the partial mediation perspective is provided by Helson's (1964) adaptation level theory, which holds that individuals perceive new stimuli (experience) as deviations from existing cognitions (i.e., new cognitions) are viewed as a shift from their prior baseline or reference levels (*adaptation levels*). Hence, new cognitions tend to remain in the general vicinity of prior cognitions (*homeostatis*), adjusted appropriately for any new positive or negative stimuli. Keeping with these considerations, later-stage cognitions can be viewed as an additive function of prior cognitions plus the deviation or discrepancy from those levels due to actual experience. Hence, we hypothesize usage-stage belief as the joint outcome of pre-usage belief and disconfirmation, and usage-stage attitude as being determined jointly by pre-usage attitude and satisfaction (see Figure 1). Note that pre-usage beliefs may be determined by a combination of externally communicated information (e.g., available IT features) and other factors (e.g., personal innovativeness) that are beyond the scope of this study.

The effects of disconfirmation and satisfaction on consequent belief and attitude may continue to recur over time as users gain additional IT usage experience and thereby revise their prior cognitions in an iterative manner. However, such changes are believed to occur more during the initial phases of IT usage as the user moves from the pre-usage to usage phase, and wear out with time as users' cognitions stabilize and become more realistic based on repeated interactions with the target system (Szajna and Scamell 1993). At least one marketing study (Boulding et al. 1993) provides initial empirical evidence supporting this "wearing out" effect. Hence, the two-stage model of belief and attitude change may be extended into a three-period model (i.e., t_1 during the pre-usage stage, and t_2 and t_3 during later usage stages), whereby the magnitudes of disconfirmation, satisfaction, belief change, and attitude change are expected to decrease in magnitude from the t_1–t_2 period to the t_2–t_3 period (Szajna and Scamell 1993). Extending the original two-period

EDT model to multi-period models is our value-added contribution to the EDT literature.

Research Methodology

The hypothesized research model (Figure 1) was tested empirically using two longitudinal studies of IT usage. The first study examined computer-based tutorial (CBT) usage in end-user training contexts across three time periods (ending in t_1, t_2, and t_3), while the second study examined rapid application development (RAD) software usage an IT development context across two time periods (ending in t_1 and t_2). Collectively, the two studies allowed us to examine the robustness and generalizability of our hypothesized model across multiple technologies and IT usage contexts.

Study 1: Computer-Based Training Software Usage

The first study involved a three time-period survey of CBT usage among undergraduate IS students enrolled in multiple sections of a data communications class in a large public university. CBT is a Web-enabled training software intended to guide IT users through a self-paced, structured learning process in a multimedia environment. It is believed to significantly improve learning retention rates and reduce time to learn by 30 to 50 percent over instructor-led training (Carlton 2001), and is increasingly being used by businesses as a cost-efficient way of providing training-on-demand on new technologies to employees across geographical locations.

At the time of the study, CBT was being introduced in this university to supplement classroom-based instruction and help students self-learn IT concepts or software that were not covered in the formal curriculum. Subjects had Web-based access to over 250 CBT modules covering a wide range of content including programming languages (e.g., C++, Java), databases (e.g., Oracle, SQL server), telecommunication concepts (e.g., TCP/IP, local area networks), system development methodologies (e.g., UML, CASE), and Web development languages (e.g., HTML, ASP, XML). While some subjects were aware of CBT, most students had no first-hand experience with CBT prior to this study.

At the beginning of the semester (time t_1), one of the authors provided a brief in-class introduction to CBT to the intended subjects, describing the benefits of CBT and its relevance to their curriculum and professional careers, and guided them through one CBT module to help them appreciate and understand its usage. Following the introduction, subjects completed a questionnaire that assessed their pre-usage usefulness perceptions and attitude. Students were then asked to complete a short assignment, which required them to use one of the CBT modules. Two or three weeks later (at time t_2,), students completed a second questionnaire that measured their disconfirmation and satisfaction with CBT usage, along with modified perceptions of usefulness, attitude, and usage intention. Although CBT usage was encouraged after the initial exercise, usage thereafter was voluntary. After another nine or ten weeks (at time t_3), students completed a third questionnaire that reassessed their perception of disconfirmation, satisfaction, usefulness, attitude, and usage intention. Responses from the three surveys were matched to create a single record for each respondent. Subjects also provided qualitative responses on what they liked or disliked about their CBT usage experience, whether their initial expectations of CBT usage were met, and whether they might use the software again at a later time. The total duration of the study was approximately three months.

Over three semesters, we obtained 189 responses at time t_1, 175 responses at time t_2, and 172 responses at time t_3. Nonresponse bias was not a concern since most respondents at time t_1 also completed the survey at times t_2 and t_3. However, the disconfirmation construct at time t_3 was collected only during the third semester of the study, limiting it to only 54 responses and reducing the effective sample size for statistical analysis involving this construct.

Study 2: Rapid Application Development Tool Usage

The second study examined RAD software usage among graduate students enrolled in evening sections of an electronic commerce course at a second public university. RAD tools are gaining increasing acceptance in firms as a means of quickly building functional prototypes and sometimes full-scale applications by virtue of their ability to generate code with minimal front-end coding. A RAD software called ColdFusion was introduced in this course to provide students with hands-on experience on building e-commerce Web sites. Subjects' use of ColdFusion was recommended but voluntary, and they were free to use other comparable tools, such as FrontPage, Notepad, Visual Studio, or any word processing software of their choice, to accomplish the assigned task.

Data for this study was collected at two time points. Perceived usefulness and attitude were measured at time t_1, following a demonstration of ColdFusion and websites built using ColdFusion. Subjects were then given two weeks of hands-on instruction in ColdFusion and asked to construct a set of non-transactional HTML pages with or without using ColdFusion. All but one subject used ColdFusion (this person, who used FrontPage, was dropped from the sample). Following this task, subjects' disconfirmation and satisfaction with ColdFusion usage and their perceived usefulness, attitude, and intention to continue using ColdFusion was assessed at time t_2, one month after the first survey. A total of 77 matched responses were obtained from this study.

The RAD study differed from the CBT study in four ways. First, the technology context and hence target users were different. While CBT is a training software meant for end-users, RAD is an application development tool used by system developers. This difference allowed us the opportunity to examine the robustness and generalizability of our proposed model across two distinct IT usage contexts. Second, subjects in the first study were undergraduate students, while those in the second study were graduate students in IS with prior programming and database experience (prerequisites for this course). Many subjects in the latter group were employed full-time as system analysts or application developers in local banks, software firms, technology firms, and the U.S. Army. Third, the CBT data was collected at three points in time (enabling us to study belief and attitude changes from t_1–t_2 to t_2–t_3), while the RAD data was collected at two points in time (i.e., examined only t_1–t_2 changes). Finally, the CBT study required the students to complete one assignment using CBT followed by voluntary use, while for the RAD study, the choice of technology for completing the assignment was voluntary from the start. As noted before, one subject chose not to use ColdFusion in the RAD study.

Instrument Construction and Validation

Measurement Scales

Five constructs were of interest to this study: perceived usefulness (belief), attitude, intention, disconfirmation, and satisfaction. In the CBT study, the first two constructs were measured at time points t_1, t_2, and t_3, while the latter three constructs were measured at t_2 and t_3 only. In the RAD study, belief and attitude were measured at time points t_1 and t_2, and the remaining constructs were measured at time t_2 only. Scale items are listed in the appendix.

Usefulness, attitude, and intention were measured using pre-validated scales adapted from prior IT usage literature (e.g., Davis et al. 1989; Karahanna et al. 1999; Taylor and Todd 1995b; Venkatesh and Davis 2000). Usefulness was measured using a four-item Likert scale that examined subjects' perceptions of performance, productivity, effectiveness, and overall usefulness from using the the target IT. Attitude was measured using a four-item semantic differential scale anchored between adjective pairs "bad idea… good idea," "foolish move…wise move," "negative step…positive step," and "ineffective idea… effective idea." Since CBT software is used to learn about new technologies and acquire new software skills, CBT usage intention was measured using two Likert-scaled items that asked subjects whether they intend using the software to learn new technologies and acquire new skills, plus a third item assessing overall intent to use CBT for the remainder of the semester. Likewise, since RAD tools are used to generate and debug program code, RAD usage intention was measured by examining subjects' intent to use the tool to write code and to debug code, plus one overall usage intention item. Item wording was adapted appropriately depending on whether we were referring to the expected (at time t_1) or realized (at times t_2 and t_3) nature of the focal construct, and the IT being studied (CBT or RAD).

Disconfirmation refers to the extent to which subjects' pre-usage expectation of technology usage is contravened during actual usage experience. Although this construct has been measured in prior studies using both perceptual and inferred terms, Yi (1990) recommends the former as the more accurate measure of the construct.[3] Oliver's (1980) perceived disconfirmation scale was adapted for this purpose. Since expected benefits from IT use were previously captured using four items in the usefulness scale (performance, productivity, effectiveness, and overall usefulness), disconfirmation was assessed using four perceptual items that compared subjects' realized levels of each usefulness item against their pre-usage expected levels along seven-point Likert scales anchored between "much worse than expected" and "much better than expected." Note that the mid-point on this scale (4) denotes neutral or zero disconfirmation, and the two end-points (1 and 7) represent strongly negative and positive disconfirmation respectively.

Satisfaction, an individual's emotional state following IT usage experience, involves two dimensions: valence (positive versus negative) and intensity (Oliver 1993). Both dimensions were simultaneously assessed using four 7-point semantic differential items anchored between adjective pairs: "extremely displeased…extremely pleased," "extremely frustrated…extremely contented," "extremely terrible…extremely delighted," and "extremely dissatisfied…extremely satisfied." The original scale was used by Spreng et al. (1996) to assess consumers' satisfaction with camcorder purchase behavior, but has since been validated in the IT usage context by Bhattacherjee (2001).

Scale Validation

Scale reliability and validity were assessed via confirmatory factor analysis (CFA), performed using the partial least squares (PLS) approach. CFA is more appropriate than alternative approaches such as exploratory factor analysis in areas with strong *a priori* theory and pre-validated measurement scales (Bagozzi and Phillips 1982), as in our study. Unlike covariance-based structural equation modeling approaches such as LISREL, the variance-based PLS approach does not impose sample size restrictions or require multivariate normality distribution for the underlying data (Fornell and Bookstein 1982). Given our small sample size of 77 in the RAD study and 54 observations for the disconfirmation construct at time t_3 in the CBT study, and the inherent difficulties with establishing multivariate normality with small samples, PLS was deemed more appropriate than LISREL.[4] The analysis was performed using PLS-Graph Version 3.00 (Chin and Frye 1994), using raw data sets as inputs and modeling all scale items as reflective indicators of their corresponding latent constructs. Three separate CFA models were examined: (1) t_1–t_2 model for the CBT study, (2) t_2–t_3 model for the CBT study, and (3) t_1–t_2 model for the RAD study;

[3]Inferred disconfirmation scales measure disconfirmation as the difference score of separately assessed expectation and performance. These scales tend to suffer from low reliability, ceiling and floor effects, and expectation bias (see Yi [1990] for a discussion).

[4]Despite these concerns, we reran our CFA analysis and hypotheses testing analyses using LISREL and obtained results very similar to those of PLS.

Table 1. Confirmatory Factor Analysis Results

CBT Study (time t_1–t_2)					CBT Study (time t_2–t_3)					RAD Study (time t_1–t_2)				
Scale Item	Item Mean	Item S. D.	Item Loading	Mean Loading*	Scale Item	Item Mean	Item S. D.	Item Loading	Mean Loading*	Scale Item	Item Mean	Item S. D.	Item Loading	Mean Loading*
U11	5.14	1.09	0.94	0.93	U21	4.74	1.35	0.96	0.95	U11	5.21	0.92	0.94	0.94
U12	5.04	1.04	0.95	0.95	U22	4.61	1.36	0.94	0.94	U12	5.18	0.93	0.89	0.90
U13	5.12	1.04	0.93	0.93	U23	4.71	1.36	0.96	0.96	U13	5.19	0.92	0.93	0.93
U14	4.87	1.15	0.83	0.83	U24	4.78	1.45	0.89	0.89	U14	5.16	0.87	0.84	0.84
A11	5.82	0.98	0.93	0.93	A21	5.46	1.24	0.95	0.95	A11	6.03	0.96	0.95	0.95
A12	5.83	0.93	0.89	0.89	A22	5.42	1.24	0.96	0.96	A12	5.99	0.97	0.93	0.93
A13	5.80	1.00	0.92	0.92	A23	5.47	1.23	0.94	0.93	A13	6.05	1.13	0.95	0.95
A14	5.63	0.97	0.86	0.86	A24	5.27	1.36	0.93	0.92	A14	5.74	1.15	0.91	0.91
D21	4.33	1.26	0.95	0.94	D31	4.55	0.85	0.88	0.87	D21	4.25	1.21	0.96	0.95
D22	4.23	1.21	0.95	0.94	D32	4.40	0.84	0.93	0.92	D22	4.17	1.44	0.93	0.92
D23	4.30	1.20	0.94	0.93	D33	4.28	0.77	0.85	0.84	D23	4.22	1.46	0.93	0.93
D24	4.50	1.41	0.89	0.88	D34	4.36	0.96	0.80	0.80	D24	4.12	1.41	0.89	0.88
S21	4.94	1.39	0.94	0.93	S31	4.96	1.32	0.95	0.95	S21	4.47	1.34	0.92	0.92
S22	4.99	1.39	0.95	0.93	S32	4.99	1.34	0.96	0.96	S22	4.52	1.34	0.95	0.95
S23	4.73	1.52	0.90	0.89	S33	4.82	1.46	0.91	0.91	S23	4.45	1.35	0.94	0.94
S24	4.82	1.34	0.94	0.93	S34	4.92	1.18	0.95	0.95	S24	4.43	1.31	0.92	0.91
U21	4.74	1.35	0.95	0.95	U31	4.71	1.25	0.96	0.96	U21	4.74	0.95	0.95	0.95
U22	4.61	1.36	0.94	0.93	U32	4.57	1.32	0.95	0.95	U22	4.77	0.97	0.95	0.95
U23	4.71	1.36	0.96	0.95	U33	4.67	1.26	0.95	0.94	U23	4.82	0.96	0.93	0.94
U24	4.78	1.45	0.89	0.88	U34	4.60	1.35	0.87	0.87	U24	4.53	1.05	0.80	0.80
A21	5.46	1.24	0.95	0.94	A31	5.45	1.20	0.94	0.94	A21	4.94	0.94	0.82	0.82
A22	5.42	1.24	0.96	0.95	A32	5.44	1.13	0.95	0.95	A22	4.87	0.99	0.90	0.89
A23	5.47	1.23	0.94	0.93	A33	5.51	1.17	0.95	0.94	A23	4.83	0.85	0.84	0.84
A24	5.27	1.36	0.93	0.92	A34	5.31	1.19	0.91	0.90	A24	4.66	1.08	0.84	0.83
I21	4.77	1.59	0.96	0.95	I31	4.61	1.56	0.96	0.96	I21	4.81	1.04	0.87	0.87
I22	4.86	1.62	0.95	0.94	I32	4.65	1.54	0.95	0.95	I22	4.66	0.94	0.89	0.88
I23	4.49	1.65	0.90	0.89	I33	4.38	1.54	0.89	0.89	I23	4.49	1.05	0.84	0.83

Legend: U1n: Usefulness at time t_1; A1n: Attitude at t_1; D2n: Disconfirmation at t_2; S2n: Satisfaction at t_2; U2n: Usefulness at t_2; A2n: Attitude at t_2; I2n: Intention at t_2, D3n: Disconfirmation at t_3; S3n: Satisfaction at t_3; U3n: Usefulness at t_3; A3n: Attitude at t_3; I3n: Intention at t_3.

*Mean item loadings calculated using bootstrap algorithm with 100 subsamples; all mean loadings significant at $p < 0.01$.

Table 2. Scale Properties and Descriptive Statistics

Construct	Mean	S.D.	ρ_c	Inter-Construct Correlations*						
CBT Study (time t_1–t_2):				U1	A1	D2	S2	U2	A2	I2
U1	5.01	1.02	0.95	0.91						
A1	5.82	0.90	0.94	0.55	0.90					
D2	4.29	1.17	0.96	0.29	0.35	0.93				
S2	4.87	1.31	0.96	0.33	0.42	0.69	0.93			
U2	4.68	1.31	0.97	0.45	0.42	0.77	0.68	0.94		
A2	5.44	1.18	0.97	0.36	0.49	0.70	0.80	0.74	0.95	
I2	4.71	1.52	0.96	0.38	0.49	0.75	0.70	0.82	0.75	0.94
CBT Study (time t_2–t_3):				U2	A2	D3	S3	U3	A3	I3
U2	4.68	1.31	0.97	0.94						
A2	5.44	1.18	0.97	0.74	0.95					
D3	4.36	0.81	0.92	0.45	0.44	0.87				
S3	4.92	1.25	0.97	0.59	0.58	0.46	0.94			
U3	4.63	1.22	0.96	0.65	0.61	0.60	0.64	0.93		
A3	5.46	1.12	0.96	0.63	0.69	0.54	0.80	0.71	0.94	
I3	4.54	1.44	0.95	0.63	0.58	0.52	0.53	0.79	0.61	0.93
RAD Study (time t_1–t_2):				U1	A1	D2	S2	U2	A2	I2
U1	5.26	0.86	0.94	0.91						
A1	6.02	0.98	0.96	0.22	0.93					
D2	4.42	0.95	0.96	-0.34	-0.12	0.93				
S2	4.54	1.11	0.96	-0.32	-0.19	0.79	0.93			
U2	4.77	0.92	0.95	-0.07	0.03	0.73	0.55	0.91		
A2	4.88	0.81	0.91	-0.20	-0.14	0.68	0.80	0.67	0.85	
I2	4.65	0.88	0.90	-0.05	-0.02	0.74	0.65	0.81	0.69	0.87

Legend: U1: Usefulness at time t_1; A1: Attitude at t_1; D2: Disconfirmation at t_2; S2: Satisfaction at t_2; U2: Usefulness at t_2; A2: Attitude at t_2; I2: Intention at t_2, D3: Disconfirmation at t_3; S3: Satisfaction at t_3; U3: Usefulness at t_3; A3: Attitude at t_3; I3: Intention at t_3.

*Diagonal elements represent square root of AVE for that construct.

each model consisting of seven latent constructs and 27 indicator items. Since PLS-Graph limits the number of input indicator items to 30, we had to split our CFA analysis for the CBT study into two sub-models for t_1–t_2 and t_2–t_3 time periods. Significance analysis was performed using a bootstrap algorithm with 100 subsamples. Results of the CFA analyses for all three models are listed in Tables 1 and 2.

Scale validation proceeded in two phases: convergent validity and discriminant validity analyses. Convergent validity of scale items was assessed using three criteria recommended by Fornell and Larcker (1981): (1) all item factor loadings (λ) should be significant and exceed 0.70, (2) composite construct reliabilities should be greater than 0.80, and (3) average variance extracted (AVE) for each construct should exceed the variance attributable to measurement error (i.e., AVE = 0.50). As shown in Table 1, standardized CFA loadings for all scale items in all three models were significant at $p < 0.001$ and exceeded the minimum loading criterion of 0.70. From Table 2, we can see that composite reliabilities (ρ_c) of all factors also exceeded the required minimum of 0.80. Further, AVE values of all constructs in the three models exceeded the threshold value of 0.50 (see square roots of AVE values listed along the principal diagonals of the correlation matrices in Table 2). Hence, all three conditions for convergent validity were met.

Discriminant validity between constructs was examined using Fornell and Larcker's recommendation that the square root of AVE for each construct should exceed all correlations between that and other constructs. This test is supposedly a stronger test of discriminant validity than pair-wise comparison of χ^2 values of unconstrained and constrained CFA models often reported in the literature (Fornell and Larcker 1981). From the data presented in Table 2, we can see that the highest correlation between any pair of constructs in the three CFA models was 0.82 (between usefulness and intention constructs at time t_2 in the CBT study), while the lowest square root of AVE was 0.85 (corresponding to attitude at time t_2 in the RAD study). Hence, the discriminant validity criterion was also met for all three CFA models, giving us further confidence in the adequacy of our measurement scales.

Data Analysis and Results

Data analysis proceeded in four stages. First, we compared construct means for usefulness, attitude, disconfirmation, and satisfaction at times t_1, t_2, and t_3 (for both CBT and RAD studies) to examine if and how they changed over time. Next, we analyzed hypothesized associations in our research model using partial least squares (PLS) for CBT and RAD data. Third, unexpected results derived from the PLS analysis was reconciled using additional *post hoc* analysis. Finally, qualitative responses obtained from CBT respondents were content analyzed to triangulate or validate our quantitative results and/or gain new insights.

Comparison of Construct Means

To compare whether subjects' usefulness and attitude perceptions changed from time t_1 to t_2 or t_3, we aggregated item responses for each construct at each time period and compared the mean aggregated scores pair-wise via a series of t-tests. The results are provided in Table 3. Subjects' mean usefulness perceptions regarding CBT usage dropped from 5.06 at time t_1 to 4.65 at time t_2 ($t = 4.06$, $p < 0.001$), and attitude means dropped from 5.81 to 5.43 during that time ($t = 4.69$, $p < 0.001$). These changes supported our expectation that users' cognitions regarding IT usage do indeed change with time. However, from t_2 to t_3, the change in usefulness means (from 4.75 to 4.63) and attitude means (from 5.45 to 5.46) were both nonsignificant ($t = 1.36$ and -0.14 respectively). This is again consistent with theoretical expectations from CDT, which presumes cognition changes to wear out over time as subjects form more realistic and accurate expectations of IT usage, by virtue of their first-hand experience, and are also able to realize those expectations. This finding also confirms that the rates of belief and attitude changes are time-variant and more predominant during early stages of IT usage than in the later stages.

For the RAD study, subjects' mean usefulness perceptions dropped from 5.26 at time t_1 to 4.77 at t_2 ($t = 3.31$, $p < 0.001$) and mean attitude dropped from 6.02 at t_1 to 4.88 at t_2 ($t = 7.59$, $p < 0.001$). These changes mirrored corresponding (t_1–t_2) changes in the CBT study, providing further evidence of the occurrence of belief and attitude changes across technologies and usage contexts. Although the magnitude of usefulness change in the RAD study (t_1–t_2) was comparable to that of the CBT study, the attitude change was much larger in RAD, suggesting that the rate of cognition changes may also vary with technological differences.

Path Analysis

The next step in our data analysis was to examine the significance and strength of hypothesized effects in our research model (Figure 1) and compare relative effect sizes for common dependent variables. This was done using PLS-Graph, using the same three models used for CFA earlier: initial (t_1–t_2) CBT usage, later (t_2–t_3) CBT usage, and initial (t_1–t_2) RAD usage. As in the CFA analysis, the CBT analysis was split into two sub-models in light of system limitations in PLS-Graph. Since we did not have any direct associations between constructs at t_1 and t_3, creating two sub-models did not affect our analysis. Results of the analysis for the three models, including path

Table 3. Comparison of Means

		1		2		Diff (1-2)		t-statistic	p-value
Test (Study)	N*	Mean**	S.D.	Mean	S.D.	Mean	S.D.		
U1 ≠ U2 (CBT)	169	5.06	1.02	4.65	1.31	0.41	1.32	4.06	0.000
U2 ≠ U3 (CBT)	154	4.75	1.34	4.63	1.26	0.12	1.10	1.36	0.173
A1 ≠ A2 (CBT)	169	5.81	0.86	5.43	1.19	0.38	1.06	4.69	0.000
A2 ≠ A3 (CBT)	154	5.45	1.17	5.46	1.13	–0.01	0.93	–0.14	0.885
U1 ≠ U2 (RAD)	77	5.26	0.86	4.77	0.92	0.49	1.29	3.31	0.001
A1 ≠ A2 (RAD)	77	6.02	0.98	4.87	0.81	1.14	1.32	7.59	0.000

Legend: U1: Usefulness at time t_1; A1: Attitude at t_1; U2: Usefulness at t_2; A2: Attitude at t_2; U3: Usefulness at t_3; A3: Attitude at t_3.

*Sample size varied across tests due to missing values.
**Pair-wise means (slightly different from overall sample means in Table 2 due to missing values).

coefficients, path significances, and variance explained (R^2 values) for each dependent variable, are shown in Figures 2, 3, and 4.

For the initial (t_1 –t_2) CBT usage model (see Figure 2), all hypothesized paths were significant at $p < 0.05$. Usefulness and attitude at time t_2 jointly explained 73 percent of the variance in CBT usage intention at time t_2, with usefulness contributing to most of that explanation ($\beta = 0.59$). About 65 percent of the variance in usefulness at time t_2 was explained by disconfirmation beliefs at t_2 ($\beta = 0.70$) and usefulness at time t_1 ($\beta = 0.24$), suggesting that disconfirmation is more critical in the formation of modified usefulness than prior usefulness perceptions. Likewise, 73 percent of the attitude variance at time t_2 was explained by satisfaction at t_2 ($\beta = 0.52$), usefulness at time t_2 ($\beta = 0.32$), and attitude at time t_1 ($\beta = 0.14$), suggesting that satisfaction is more critical in the formation of modified attitudes than prior attitudes. Collectively, these effects attest to the importance of the emergent constructs (disconfirmation and satisfaction) in shaping usefulness and attitude changes among IT users.

Among other associations in this model, only 9 percent of disconfirmation at time t_2 was explained by usefulness at time t_1 ($\beta = 0.29$), suggesting that disconfirmation depends less on initial expectations and possibly more on constructs related to the interim IT usage experience (e.g., performance) not examined here. Further, 49 percent of the satisfaction at time t_2 was explained by disconfirmation at time t_2 ($\beta = 0.65$) and usefulness at time t_1 ($\beta = 0.14$). The weak direct effect of initial usefulness on satisfaction, coupled with the strong effect of disconfirmation, suggested that one's satisfaction with IT usage is determined more by one's realized disconfirmation (based on actual experience) than by initial expectations of the system. Finally, attitude at time t_1 was explained significantly by usefulness at time t_1 ($\beta = 0.55$), consistent with prior IT usage research.

For the later (t_2–t_3) CBT usage model (Figure 3), 63 percent of CBT usage intention at time t_3 was explained by usefulness ($\beta = 0.71$) and attitude ($\beta = 0.12$) at time t_3. Usefulness at time t_3, in turn, was determined by disconfirmation at time t_3 ($\beta = 0.39$) and usefulness at time t_2 ($\beta = 0.48$), for a combined R^2 of 55 percent. The smaller effect of disconfirmation relative to usefulness in this model (the opposite of the early-stage CBT model) is consistent with cognitive dissonance theory, which predicts that one's beliefs tend to stabilize as dissonance (disconfirmation) effects wear off over time. However, attitude at time t_3 continued to be explained largely by satisfaction at t_3 ($\beta = 0.50$) rather than by attitude at t_2 ($\beta = 0.27$) or useful-

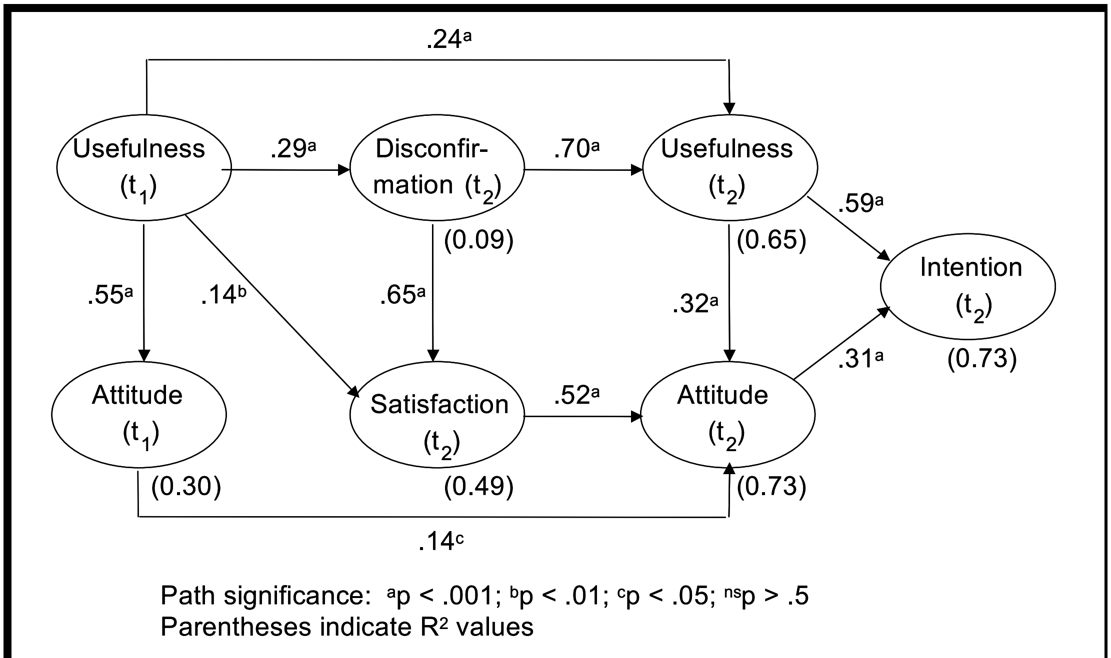

Figure 2. PLS Analysis of Initial CBT Usage

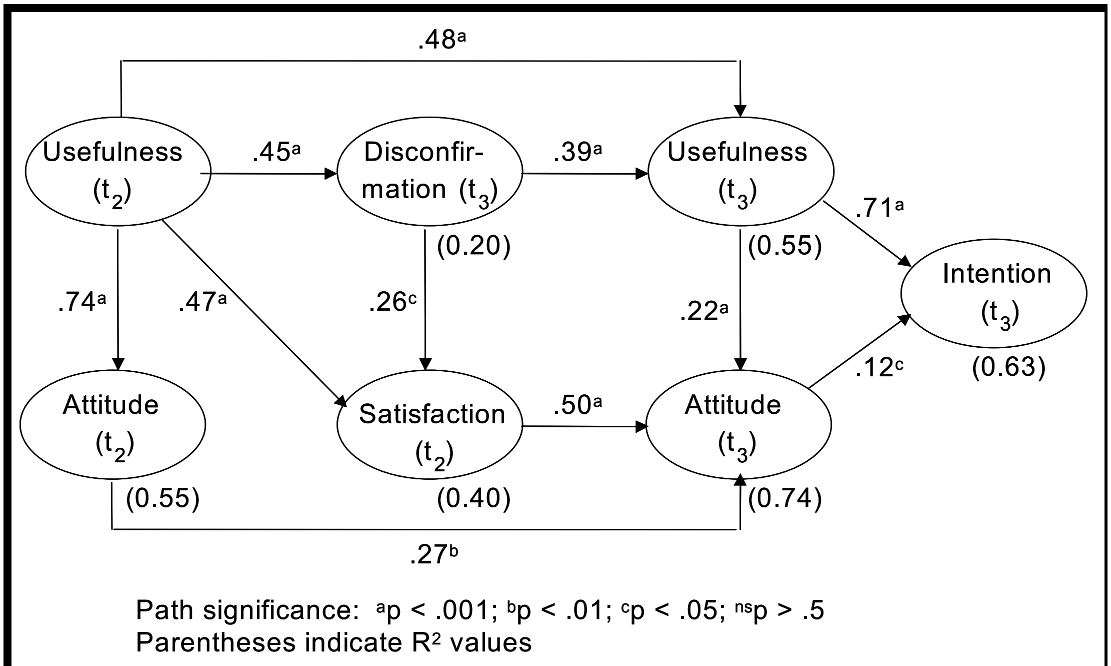

Figure 3. PLS Analysis of Later CBT Usage

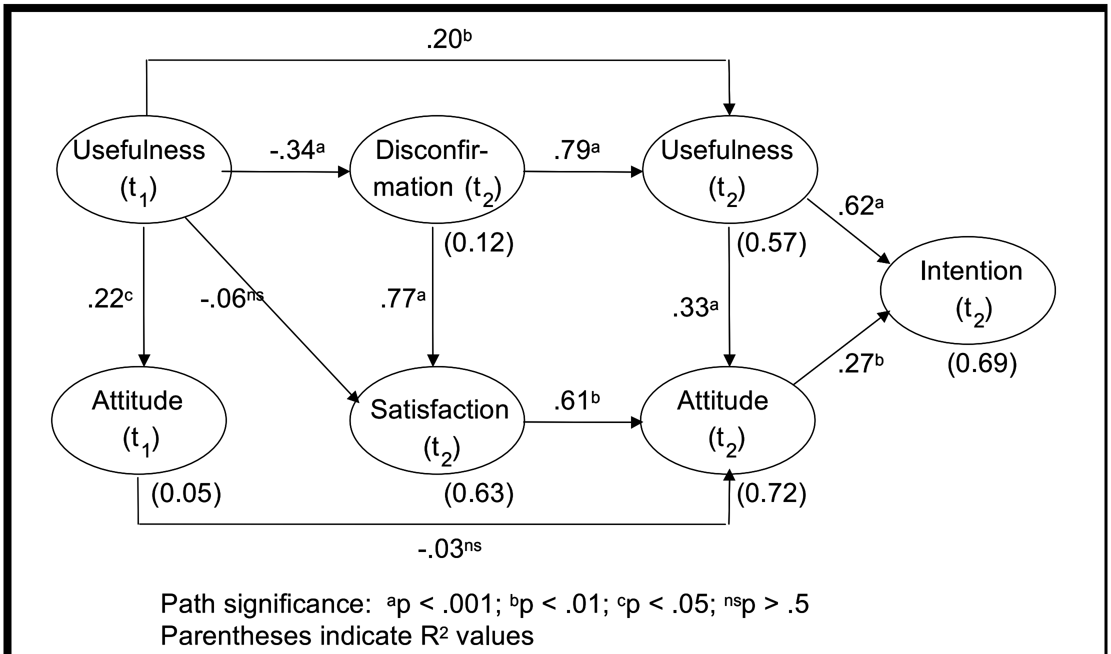

Figure 4. PLS Analysis of Initial RAD Usage

ness at t_3 (β = 0.22), for a joint R^2 of 74 percent. Disconfirmation at time t_3 was significantly influenced by usefulness at t_2 (β = 0.45; R^2 = 20 percent), this effect increasing from the prior model as usefulness perceptions and level of disconfirmation seem to have stabilized over time. Also, satisfaction at time t_3 was explained more by usefulness at t_2 (β = 0.47) than by disconfirmation (β = 0.26), reflecting a greater impact of stabilized usefulness perceptions on satisfaction affect as well. Usefulness and attitude at time t_2 were also strongly correlated with a path coefficient of 0.74 and R^2 value of 55 percent.

For the initial (t_1–t_2) RAD usage model (Figure 4), 69 percent of the variance in RAD usage intention at time t_2 was explained by usefulness at t_2 (β = 0.62) and attitude at t_2 (β = 0.27), similar to the pattern of relative effects in the initial CBT model. Usefulness at t_2 was explained mostly by disconfirmation (β = 0.79) and to a lesser extent by usefulness at t_1 (β = 0.20), for a joint R^2 of 57 percent, mirroring a similar pattern in the CBT study. Also consistent with our expectations, 72 percent of the variance in attitude at t_2 was explained by satisfaction (β = 0.61) and usefulness at t_2 (β = 0.33). These findings demonstrated that the salience of emergent constructs (disconfirmation and satisfaction) in shaping subsequent belief and attitude is generalizable across technology and usage contexts. Similar to the CBT study, disconfirmation at time t_2 had a strong effect (β = 0.77) on satisfaction at t_2, while usefulness at t_1 had no significant effect. However, contrary to the CBT study, we observed a significant *negative* association between usefulness at time t_1 and disconfirmation at t_2 (β = –0.34), reasons for which are explored in the next section.

In summary, despite some variations between individual path coefficients, the RAD model results largely corroborated our findings from the initial CBT usage model, establishing the salience of disconfirmation and satisfaction in driving belief and attitude changes and the generalizability of our hypothesized model across technologies and usage contexts.

Post Hoc Analysis

The preceding analysis revealed some unexpected findings that warranted further investigation. First, pre-usage usefulness (belief) had a negative effect (β = -0.34) in our initial (t_1–t_2) RAD study (as expected), but a positive effect on disconfirmation (β = 0.29) in the t_1–t_2 CBT study (see Figures 2 and 4). Second, in both CBT and RAD studies, aggregate usefulness and attitude means dropped from time t_1 to t_2 (usefulness from 5.01 to 4.68; attitude from 5.82 to 5.44) despite positive (i.e., greater than 4.0) disconfirmation (4.29) and satisfaction (4.87) at time t_2 (see Table 2). Third, in the CBT study, disconfirmation mean increased from 4.29 at time t_2 to 4.36 at t_3 (see Table 2) and mean satisfaction increased from 4.87 to 4.92, although we expected these constructs to wear out with time (i.e., regress toward neutral disconfirmation of 4.0). We explore possible reasons for these counterintuitive effects below.

To understand why pre-usage belief and disconfirmation were negatively related in the RAD study but positively related in the CBT study, we "drilled down" on our dataset using two dimensions: subjects' pre-usage usefulness expectations (i.e., whether their initial expectation was greater or lower than the average for the entire sample) and disconfirmation valence (i.e., whether their aggregate disconfirmation score at time t_2 was higher or lower than the scale's neutral point of 4). Based on these dimensions, subjects were classified into four subgroups: (1) those with high initial expectations and positive disconfirmation of those expectations (presumably due to positive usage experience), (2) those with high expectations and negative disconfirmation (due to negative usage experience), (3) those with low expectations and positive disconfirmation, and (4) those with low expectations and negative disconfirmation. CBT subjects were represented in groups 1 (high initial expectations mean of 5.21 in Table 4 versus overall sample mean of 5.01 in Table 2, but positive disconfirmation) and 4 (low expectations mean of 4.70 versus sample mean of 5.01, and negative disconfirmation), while RAD subjects reflected groups 2 (high expectations mean of 5.88 versus sample mean of 5.26, and negative disconfirmation) and 3 (low expectations mean of 5.10 versus sample mean of 5.26, and positive disconfirmation). Viewing groups 2 and 3 as being more likely, EDT posits a negative relationship between initial expectations and disconfirmation, as observed in our RAD sample. However less common, groups 1 and 4 are also feasible if high expectations are positively disconfirmed and low expectations are negatively disconfirmed, as was observed among our CBT subjects. It thus appears that the direction of the effect between pre-usage expectation (usefulness) and disconfirmation depends on the extent of variation of the expectation from the mean and the nature of experience with the product, rather than on the magnitude of initial expectation, further validating disconfirmation as an experience-based emergent construct.

To better understand why mean usefulness and attitude dropped from time t_1 to t_2 in both CBT and RAD studies when subjects experienced overall positive disconfirmation and satisfaction, we extended our subgroup analysis to compare usefulness and attitude means at time periods t_1 and t_2 separately for positively and negatively disconfirmed subjects at time t_2 (see Table 4). The positively disconfirmed group in the CBT study had a usefulness mean of 5.21 at t_1, which *increased* to 5.35 at t_2, consistent with the theoretical prediction that positive disconfirmation tends to cause an upward revision of IT users' usefulness beliefs. In contrast, mean usefulness in the negatively disconfirmed group decreased from 4.70 at t_1 to 3.24 at t_2, again consistent with our expectation that negative disconfirmation causes a downward revision of user beliefs. The magnitude of belief change was larger among the negatively disconfirmed group, possibly due to a high net negative disconfirmation (2.69—4.00 = –1.31) for these subjects, compared to a smaller belief change and smaller net positive disconfirmation (5.06—4.00 = 1.06) among the positive disconfirmation group. Likewise, in the RAD study, mean usefulness increased from 5.10 at time t_1 to 5.38 at time t_2 for the positive disconfirmation group

Table 4. Subgroup Analysis

	Disconfirmation (t_2) in CBT Study		Disconfirmation (t_2) in RAD Study	
	Positive	Negative	Positive	Negative
Number of Observations	89	28	31	11
Usefulness (t_1)	5.21	4.70	5.10	5.88
Usefulness (t_2)	5.35	3.24	5.38	4.15
Usefulness (t_3)	5.09	3.32	-	-
Disconfirmation (t_2)	5.06	2.69	5.36	3.20
Disconfirmation (t_3)	4.56	3.75	-	-
	Satisfaction (t_2) in CBT Study		Satisfaction (t_2) in RAD Study	
	Positive	Negative	Positive	Negative
Number of Observations	124	32	37	13
Attitude (t_1)	5.92	5.38	5.89	6.54
Attitude (t_2)	5.97	4.09	5.39	4.08
Attitude (t_3)	5.28	4.43	-	-
Satisfaction (t_2)	5.53	2.84	5.43	3.10
Satisfaction (t_3)	5.28	3.78	-	-

and decreased from 5.88 at t_1 to 4.15 at t_2 for the negative disconfirmation group, which was also consistent with theoretical expectations. Hence, the drop in overall usefulness mean from t_1 to t_2 for the entire sample (CBT or RAD) despite slightly positive disconfirmation was possibly an artifact of pooling together positively and negatively disconfirmed subjects into a single group.

A similar analysis was performed to investigate the drop in attitude from t_1 to t_2 by separating users into positive and negative satisfaction groups (since satisfaction is an affect similar to attitude, unlike disconfirmation). Positively satisfied CBT users experienced a slight increase in attitude from 5.92 at time t_1 to 5.97 at time t_2, while negatively satisfied (dissatisfied) users experienced a decrease in attitude from 5.38 to 4.09 during that period (see Table 4). However, for the RAD study, both positive and negative satisfaction groups recorded a drop in attitudes from t_1 to t_2, with the former group registering a small drop from 5.89 to 5.39 relative to the latter dropping from 6.54 to 4.08. Interestingly, the neutral group (aggregate satisfaction of 4.0) in this study also saw a decrease in attitude by a magnitude intermediate between that of the positive and negative satisfaction groups (not shown in Table 4), suggesting a general tendency of temporally declining attitude for the RAD software. This idiosyncratic result may have been caused by the small group sizes in the RAD instance or by technological differences between CBT and RAD software that were not examined in this analysis.

For both CBT and RAD subjects, the magnitude of usefulness and attitude change (decrease) for negatively disconfirmed or dissatisfied subjects was much larger than that for positively disconfirmed or satisfied subjects. It may be that people react more strongly to negative experiences than to positive experiences, and hence negative disconfirmation (or dissatisfaction) may have disproportionately larger impacts on belief (or attitude) change than positive disconfirmation (or satisfaction). In other words the effects of the emergent factors on subsequent cognitions is asymmetrical. Since most CBT and RAD users entered our studies with high expectations (greater than 4), there was a greater possibility of downward revision due to a negative experience than upward revision due to a positive experience. However, the above evidence suggests the need to consider the direction of disconfirmation (apart from the magnitude of disconfirmation) in future studies of belief or attitude change.

Finally, to understand why disconfirmation and satisfaction means in the CBT study moved farther away from the neutral disconfirmation value of 4 from t_2 and t_3 when we expected this construct to regress toward the neutral value (Szajna and Scamell 1993), we compared aggregate disconfirmation and satisfaction scores at times t_2 and t_3 separately for positively disconfirmed and negatively disconfirmed (at time t_2) CBT subjects. The disconfirmation mean *decreased* from 5.06 to 4.56 for the positively disconfirmed group and increased from 2.69 to 3.75 for the negatively disconfirmed group (see Table 4). In both subgroups, mean disconfirmation regressed toward the neutral value of 4, providing evidence of the wearing out of this construct over time. Likewise, the satisfaction mean also decreased from 5.53 to 5.28 for the satisfied group and increased from 2.84 to 3.78 for the dissatisfied group, demonstrating that satisfaction too tends to wear out over time within each subgroup.

Since the CBT study required an initial period of mandatory usage (i.e., subjects were required to complete one CBT assignment), unlike the RAD study where usage was entirely voluntary, one may wonder whether some of the observed differences between these two studies can be attributed to the voluntariness (or lack thereof) of the study context. As demonstrated in the above analysis, the between-study differences were likely caused by pooling together the positively and negatively disconfirmed (or satisfied and dissatisfied) subjects, and separating out the two groups provide results that are consistent with theory across both empirical contexts. While most prior IT usage studies have been conducted in voluntary contexts, studies that have formally examined the role of voluntariness in IT usage (Venkatesh and Davis 2000) posited voluntariness as mediating the effect of normative influences (e.g., subjective norm) on users' usage intention. In other words, despite its association with intention, it does not appear that voluntariness is directly related to beliefs or attitudes per se. However, voluntariness may be a relevant construct in studies focusing on changes in intention.

The preceding analyses indicate that grouping positively disconfirmed and negatively disconfirmed subjects into a single subject pool may generate idiosyncratic results, may obscure true theoretical effects, and may have contributed to some of the conflicting results reported in the EDT literature. Separating these subjects into different subgroups provides greater insights into the complex associations between initial beliefs (attitude) and disconfirmation (satisfaction) and between disconfirmation (satisfaction) and later beliefs (attitude). We encourage future researchers to consider the above effects while designing empirical studies based on EDT.

Content Analysis of Qualitative Data

The final stage in our empirical analysis was a content analysis of CBT users' qualitative responses to a set of open-ended questions on what they liked or disliked about using CBT, whether their initial expectations from CBT usage ware met, and whether they intend using it again at a later time. The purpose of this analysis was to qualitatively triangulate and validate our earlier quantitative findings, and possibly gain additional insights into the nature and causes of the hypothesized associations. This open-ended questionnaire was administered with the final survey at time t_3 and to part of the sample with the survey at time t_2. A total of 115 textual responses were obtained, including matched responses from 12 subjects at times t_2 and t_3.

The qualitative data was content analyzed into general themes representing our constructs of interest (e.g., disconfirmation at time t_2, usefulness perceptions at time t_3, etc.). A multiple classification scheme was used such that each response could be classified into more than one category. Classification was performed independently by three judges. Two of these judges were unfamiliar with the study or its quantitative results, thereby controlling for any potential bias caused by ex ante theoretical or empirical knowledge of the study. Judges were provided with a list of all constructs of interest, along with their formal definitions, illustrative examples, and coding schemes. They were "walked through" several practice rounds to familiarize them with the coding process and then asked to independently code each response into one or more categories or an "other" category, identify the valence (positive or negative) of each category, and note any observed causation. Sample qualitative responses and their classifications are presented in Table 5 for illustrative purposes.

The three judges agreed on 73 percent of the classifications. Most discrepancies occurred when user responses did not fit well within one of the predefined categories (e.g., "CBT is okay for the right kind of people"). Upon completion of the coding process, the three judges collectively revisited each response, debating and resolving any discrepancy in its classification, until they were satisfied with a single consensus coding. As a test for semantic validity,[5] an external judge, familiar with the content analysis technique but not with the specifics of this research project, examined the final classifications for each of the 115 textual responses, and agreed that each text indeed reflected the categories in which it was placed by the three-judge panel.

Nine responses were dropped because they did not pertain directly to CBT usage (e.g., "Class assignment was easy to use and provided good information") or the judges could not collectively decipher what the respondent meant (e.g., "It is very detailed"). Of the remaining responses, 59 percent demonstrated positive perceptions toward CBT usage (e.g., "covered a large range of topics and helped me learn at my own pace"), 32 percent had negative perceptions (e.g., "it is too slow"), and 9 percent had both positive and negative perceptions. This suggested that most CBT users were somewhat positively disconfirmed with their CBT usage experience, supporting the overall disconfirmation score of 4.29 in our quantitative study.

About 68 percent of the responses tapped into the usefulness of CBT usage, either in a positive sense (e.g., "The CBT provided good visual examples which helped me out greatly") or in a negative sense (e.g., "Some of the tutorials were too long. By the time you went through to find one thing, you could have looked elsewhere"). These responses validated our choice of usefulness as the most salient belief driving IT usage behaviors and the core belief of interest to this study. However, other beliefs, such as usability (e.g., "The program takes too long to load"), lack of time (e.g., "It is helpful, but I worry that I will not have the time to use it"), and compatibility (e.g., "The software is extremely negative because I don't want to be taught by a computer"), also influenced subjects' CBT usage intentions, albeit to a lesser extent, and may have contributed to some of the unexplained variance in our PLS models.

Subject responses corroborated the central role of disconfirmation in influencing later-stage usefulness perceptions and intentions (e.g., "My expectation was met. It was what I had expected. I'll plan to use CBT to learn more later," "Used CBT for a class assignment. I don't think I learned from it. I will probably not use CBT again"), although in a few instances, the effect of disconfirmation was confounded by other variables (e.g., "I'm graduating so it will not help me anymore. But the classes I did have that used it were effective"). However, satisfaction did not emerge as a key construct in subjects' responses, but that may be due to the lack of specific questions probing into subjects' satisfaction with CBT.

[5]Semantic validity is the extent to which judges familar with the language examine texts placed in each category and agree with their derived classification (Weber 1990).

Table 5. Content Analysis of CBT User Responses*

Responses	Initial Coding: Rater 1	Initial Coding: Rater 2	Initial Coding: Rater 3	Consensus Coding
I would use CBT because it has material that is not introduced in class but is useful at work	U3(+) → I3 (+)	U3(+) → I3 (+)	U3(+) → I3 (+)	U3(+) → I3 (+)
I have used CBT for programming assignments. It helped me understand a few basic concepts better.	D3 (+) → U3 (+)	U3 (+)	U3 (+)	U3 (+)
I enjoy using CBTs because there are a large range of topics covered and it gives me the ability to learn at my own pace. The downside is it takes a lot of time and the sections are long.	U3 (+/-) → A3 (+)	U3 (+) → A3 (+)	U3 (+/-), A3 (+)	U3 (+/-) → A3 (+)
I feel the software is extremely negative because I don't want to be taught by a computer. It would be good for supplemental instruction but I didn't pay a lot money to be taught by a computer.	U3 (-) → A3 (-)	A3 (-)	A3 (-)	O → A3 (-)
CBT is okay for the right kind of people. You really have to want to know about the subject to actually learn about it.	U3 (?)	U3 (+)	O → U3 (+)	O → U3 (+)
I will plan to use it when I have some more time to do it.	O → I3 (+)	I3 (+)	O → I3 (+)	O → I3 (+)
It is helpful, but I worry that I will not have the time to use it.	U3 (+) → I3 (-)	I3 (-)	U3 (+), O → I3 (-)	U3 (+), O → I3 (-)
It was what I thought it would be.	D3 (+)	D3 (+)	D3 (+)	D3 (+)
Used CBT for a class assignment. I don't think I learnt much from it. I will probably not use CBT again.	D2 (-) → I2 (-)	D3 (-) → I3 (-)	D2 (-) → I2 (-)	D2 (-) → I2 (-)
My expectation was met. It was what I had expected. I'll plan to use CBT to learn more of the materials that were not covered in class.	D3 (+) → I3 (+)	D3 (+) → I3 (+)	D3 (+) → I3 (+)	D3 (+) → I3 (+)
I'm graduating so it will not help me any more. But the classes I did have that used it were effective.	D3 (+) → I3 (-)	D3 (+)	D3 (+), O → I3 (-)	D3 (+), O → I3 (-)
I like CBT. I was pretty busy this semester & didn't use it as much as I would have liked to, but when I did use it, it was helpful.	A3 (+), D3 (+)	D3 (+), A3 (+)	D3 (+), O → A3 (+)	D3(+), O, A3 (+)
I don't feel it improved my skills or helped me, but maybe it would be great for someone else.	D3 (-), O	D3 (-)	D3 (-)	D3 (-), O
CBT is a good resource, but can be time consuming to use. Classes should utilize it more and save on book cost.	A3 (+), U3 (-), O	U3 (+/-), O → I3	A3 (+), U3 (-/+)	A3 (+), U3 (-/+)
CBT was a better tool than I figured it would be. It was quite easy to learn new information at my own pace.**	D2 (+), U2 (+)	D2 (+) → U2 (+)	D2 (+), U2 (+)	D2 (+), U2 (+)
Used CBT for MIS435 assignment, my expectations were met.**	D3 (+)	D3 (+)	D3 (+)	D3 (+)

Coding scheme: U1: Usefulness at time t_1; A1: Attitude at t_1; D2: Disconfirmation at t_2; S2: Satisfaction at t_2; U2: Usefulness at t_2; A2: Attitude at t_2; D3: Disconfirmation at t_3; S3: Satisfaction at t_3; U3: Usefulness at t_3; A3: Attitude at t_3; I3: Intention at t_3; O: Other factors; → implies cause-effect relationship.

*A small sample of 115 qualitative responses from the CBT study; 12 subjects responded at both t_2 and t_3.
**Responses from the same subject at times t_2 and t_3.

Discussion and Conclusions

Key Findings

The research questions we set out to study were:

(1) Do users' beliefs and attitude regarding IT usage change over time?
(2) What emergent constructs drive this change?
(3) To what extent are these effects generalizable across technological and usage contexts?

Prior IT usage research provides preliminary evidence of such changes (e.g., Szajna and Scamell 1993; Venkatesh and Morris 2000), but not why or how such changes occur. We employed CDT to elaborate why user beliefs and attitude (cognitions) change as they gain first-hand experience in IT usage and EDT to articulate the role of two emergent factors (disconfirmation and satisfaction), resulting from actual usage experience, driving this change. Based on these theories, we proposed a research model of belief and attitude change and validated it using student subjects in the context of CBT and RAD usage across multiple time periods.

The empirical findings were that IT users' usefulness (the most salient belief driving IT usage) and attitude perceptions tend to fluctuate with time across both technological and usage contexts, and that such change tend to be more prevalent during the initial phases of IT usage than in the later phases. Our findings also confirm the role of disconfirmation and satisfaction in driving usefulness and belief change. In both the CBT and RAD studies, these emergent constructs explained a greater proportion of the variance in later usefulness and attitude than that explained by the prior states of these cognitions. Hence, from a user retention perspective, IT marketers are better served by devoting more resources toward creating a positive user experience (e.g., by investing in user training programs) that can aid positive disconfirmation and higher user satisfaction than by artificially inflating user expectations of a new IT. The proportion of variance in modified beliefs and attitude left unexplained in this study leaves open the possibility that additional constructs may also be relevant in explaining the dependent variables. Some of these constructs, revealed in our qualitative analysis, may include usability, compatibility, and resource constraints (e.g., lack of time). Further, some of our CBT subjects experienced slow load times with CBT due to network infrastructural constraints at the study site, suggesting that user perceptions may sometimes be compromised by implementation problems, which, when corrected, may help improve subsequent user cognitions.

Although our overall model was supported across two distinct IT usage contexts (CBT and RAD), we found three instances where our findings were inconsistent between the two empirical studies or with theoretical expectations. Additional *post hoc* analysis, where we separated positively disconfirmed subjects from negatively disconfirmed subjects and studied their effects separately, helped reconcile the above inconsistencies. This analysis provided interesting insights into the idiosyncratic nature of the disconfirmation construct and its effects on subsequent cognitions, which future research should consider while designing EDT-based studies. We hope that this study will inspire many such future studies and will provide the foundation for a temporal process model of IT usage.

Limitations of the Study

It is important to evaluate the study's results and contributions in light of its limitations. First, the use of student subjects may limit the generalizability of our findings to organizational usage of IT. However, we expect this problem to be minimal since results reported in prior IT usage studies that employed student subjects (e.g., Agarwal and Prasad 1997; Mathieson 1990; Taylor and Todd 1995a) do not appear to be systematically different from those employing organizational users (e.g., Davis et al. 1989). Many of our RAD subjects were working professionals employed full-time in the local IT industry, somewhat alleviating this concern. The undergraduate subjects in our CBT study may be representative of the younger college-educated segment of end users; however, extending our CBT results to other end-user segments may be more problematic. Unfortunately, controlled multi-period longitudinal empirical studies are often difficult to accomplish in organizational settings.

Second, longitudinal studies, by their very nature, are subject to several threats to internal validity, including history (extraneous effects affecting the outcome), maturation (subjects becoming tired, gaining experience, etc.), testing (posttest responses conditioned by subjects' memory of pretest responses), mortality (subjects dropping out during the course of the study), and regression effects (extreme scores during pretest regressing toward average scores during the posttest) (Huck et al. 1974). While no empirical study is free of these threats, we took several proactive steps to minimize their impacts in this study. Drawing from prior longitudinal studies in the IS literature (e.g., Davis et al. 1989; Venkatesh and Davis 2000), the 12-week duration of our study appears to be short enough to minimize history and maturation effects, yet long enough to avoid testing effects. Measuring belief and attitude changes at three time periods also allowed us to test for testing, mortality, and regression effects. Our high between-period response rates suggest low mortality effect, and a cursory examination of raw data on beliefs and attitudes provided no systematic evidence for regression effects.

Third, performance was excluded from our model to minimize potential confounding with disconfirmation and because the effect of performance on belief or attitude change is mediated fully by disconfirmation. However, this exclusion prevented us from shedding much light on subjects' actual experiences or their subsequent effects on disconfirmation. We hope that future research will examine the role of performance in a temporal model of belief and attitude change.

Finally, only one usage-related belief was examined in this study (i.e., perceived usefulness). We chose usefulness because it is widely considered to be the most salient belief related to IT usage, which was further confirmed in our own qualitative analysis. Whether our proposed theoretical model applies to understanding changes in other usage-related beliefs (e.g., usability, compatibility, resource constraints) is left open for future research.

Contributions for Practice

This research has unique contributions for IS practitioners, especially for electronic commerce providers (e.g., online banks, online brokerages) whose business models and revenue streams are based on long-term usage of IT products and services. Effective management of long-term usage requires *ex ante* identification of belief and attitude changes (that govern long-term usage) and understanding the key levers of such changes. Such understanding can assist in the proactive planning of intervention mechanisms (e.g., user training) for minimizing the probability and impacts of change. Given the critical role played by disconfirmation and satisfaction in the formation of later-stage user cognitions and hence long-term usage, managers should track users' disconfirmation and satisfaction levels with technology usage (at least during the initial stages of IT usage, when such change is most prevalent), identify sources of any negative disconfirmation or dissatisfaction, and intervene before dissatisfaction leads to eventual IT discontinuance.

This research also demonstrates the futility in the strategy of artifically inflating users' pre-usage expectations of a new IT, via product hype or marketing gimmicks, to increase initial attitude and usefulness perceptions and thereby IT acceptance. Although such a strategy may benefit acceptance, high expectations are often negatively disconfirmed, leading to user dissatisfaction and eventual discontinuance. Hence, while highlighting the product features, it may be more beneficial for vendors to build realistic user expectations and also help them realize those expectations.

Contributions for Research

To the best of our knowledge, this is the first study to theoretically articulate or empirically test changes in beliefs and attitude related to IT usage or the underlying drivers of such changes. We contribute to IT usage research by presenting a theoretical model to explain temporal variations in IT usage, by identifying disconfirmation and satisfaction as emergent constructs driving usage-related belief and attitude changes, and by integrating TAM constructs with EDT to build one of the earliest process models of IT usage. We hope that this study will inspire the research community to move from traditional static IT usage models (e.g., TAM, TPB, TAM2) to temporal models focusing on understanding fluctuating patterns of IT usage.

This study also contributes to the referent theory (EDT) by helping resolve some of the empirical inconsistencies reported in the EDT literature (e.g., mixed association between initial expectation and disconfirmation, the paradox of decreasing beliefs and positive disconfirmation), and by elaborating temporal changes in the disconfirmation construct. Prior empirical inconsistencies in EDT were resolved by separating positively and negatively disconfirmed groups and demonstrating that EDT's theoretical predictions hold consistently within each group. In doing so, we elaborate the complex interrelationships between disconfirmation, expectations (beliefs), and satisfaction, which are not purely additive as described in much of the extant EDT literature. We also demonstrate, based on our three time-period CBT results, that the magnitude of disconfirmation perceptions decrease or wears off over time, possibly resulting in smaller and smaller changes in beliefs and attitudes as these constructs stabilize to realistic levels and achieve steady state equilibrium.

Finally, our study also contributed methodologically to the IS literature in that we present one of the few three time-period studies of IT usage (for the CBT study), test our theoretical model in two different empirical settings, and provide an illustration of combining quantitative and qualitative approaches to IS research. Such multi-period, multi-context, and multi-method study is particularly important for understanding complex temporal behaviors such as IT usage, and will hopefully pave the way for additional studies of this type. Our three-period model allowed us to examine not only beliefs and attitude changes over time, but also the *rate* of such changes across time from early to later stages of IT usage. Empirical validation of our model in two different IT usage contexts helped us tease out unique differences that provided us with additional opportunities for theory refinement. Our combination of quantitative and qualitative approaches helped us triangulate and validate quantitative results, but has the further potential of providing unique insights to complex temporal processes such as IT usage.

In summary, this study proposed a theoretical model of belief and attitude change among IT users, articulating disconfirmation and satisfaction as two emergent constructs driving this change, and validated the hypothesized model using survey data from two longitudinal studies in two technological and IT usage contexts. We suggest that these emergent factors are critical to understanding temporally changing patterns of IT usage patterns, and recommend that they be integrated into future process models of long-term IT usage.

Acknowledgements

The authors gratefully acknowledge valuable suggestions and feedback provided by the senior editor, associate editor, and three anonymous reviewers on earlier drafts of this paper.

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Appendix

Questionnaire Items

Usefulness (t_1):
1. Using CBT will improve my performance (Strongly disagree … Strongly agree).
2. Using CBT will increase my productivity (Strongly disagree … Strongly agree).
3. Using CBT will enhance my effectiveness (Strongly disagree … Strongly agree).
4. CBT will be useful for my studies (Strongly disagree … Strongly agree).

Attitude (t_1):
All things considered, using CBT will be a ___
1. Bad idea … Good idea.
2. Foolish move … Wise move.
2. Negative step … Positive step.
4. Ineffective idea … Effective idea.

Disconfirmation (t_2, t_3):
Compared to my initial expectations the ability of CBT ___
1. To improve my performance was (much worse than expected … much better than expected).
2. To increase my productivity was (much worse than expected … much better than expected).
3. To enhance my effectiveness was (much worse than expected … much better than expected).
4. To be useful for my studies was (much worse than expected … much better than expected).

Satisfaction (t_2, t_3):
I am ___ with my use of CBT.
1. Extremely displeased … Extremely pleased.
2. Extremely frustrated … Extremely contented.
3. Extremely terrible … Extremely delighted.
4. Extremely dissatisfied … Extremely satisfied.

Usefulness (t_2, t_3):
1. Using CBT improves my performance (Strongly disagree … Strongly agree).
2. Using CBT increases my productivity (Strongly disagree … Strongly agree).
3. Using CBT enhances my effectiveness (Strongly disagree … Strongly agree).
4. I find CBT to be useful for my studies (Strongly disagree … Strongly agree).

Attitude (t_2, t_3):
All things considered, using CBT is a ___
1. Bad idea … Good idea.
2. Foolish move … Wise move.
3. Negative step … Positive step.
4. I have an (extremely negative … extremely positive) attitude toward CBT use.

Intention (t_2, t_3):
1. I plan to continue using CBT to learn about new technologies (Strongly disagree … Strongly agree).
2. I intend to continue using CBT to learn new software skills (Strongly disagree … Strongly agree).
3. I plan to continue using CBT after this class (Strongly disagree … Strongly agree).