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EXPECTATION DISCONFIRMATION AND TECHNOLOGY ADOPTION: POLYNOMIAL MODELING AND RESPONSE SURFACE ANALYSIS[1]

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Abstract

Individual-level information systems adoption research has recently seen the introduction of expectation–disconfirmation theory (EDT) to explain how and why user reactions change over time. This prior research has produced valuable insights into the phenomenon of technology adoption beyond traditional models, such as the technology acceptance model. First, we identify gaps in EDT research that present potential opportunities for advances—specifically, we discuss methodological and analytical limitations in EDT research in information systems and present polynomial modeling and response surface methodology as solutions. Second, we draw from research on cognitive dissonance, realistic job preview, and prospect theory to present a polynomial model of expectation–disconfirmation in information systems. Finally, we test our model using data gathered over a period of 6 months among 1,143 employees being introduced to a new technology. The results confirmed our hypotheses that disconfirmation in general was bad, as evidenced by low behavioral intention to continue using a system for both positive and negative disconfirmation, thus supporting the need for a polynomial model to understand expectation disconfirmation in information systems.

Keywords: Polynomial modeling, response surface methodology, nonlinear modeling, difference scores, direct measures, technology acceptance model, expectation disconfirmation theory, IS continuance

Introduction

Organizations invest in information technology expecting positive economic returns and enhanced productivity (Brynjolfsson and Hitt 1996; Santhanam and Hartono 2003). While IT-related investments have continued to grow (Mitra 2005), the problem of underutilized systems remains (Morris and Venkatesh 2010; Forrester Research 2005). Prior research has shown that the benefits of IT investments are often obstructed by users' unwillingness to use available systems (e.g., Devaraj and Kohli 2003; Venkatesh and Davis 2000). Such low use of the installed systems has been suggested as one of the causes for the so-called "productivity paradox" (see Devaraj and Kohli 2003). Although initial user acceptance is important, productivity benefits typically accrue in the sus-

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tained use stage (see Kim and Malhotra 2005; Venkatesh et al. 2003). Users could form positive initial judgments about a system but such judgments may then be modified over time that in turn may result in users discontinuing the use of the system after initial acceptance, thus possibly resulting in little or no long-term productivity gains. Therefore, furthering our understanding of the initial acceptance and subsequent discontinuance anomaly is of value to researchers and practitioners alike.

A vast body of research studying technology acceptance and use exists, with some research on the evolution of acceptance over time (for a review, see Venkatesh et al. 2007; Venkatesh et al. 2003). There is also some evidence to suggest that the determinants of initial user acceptance are different from the determinants of continued usage (Karahanna et al. 1999; Venkatesh and Morris 2000). This stream of research has recently seen the introduction of a new theoretical perspective drawn from psychology, expectation–disconfirmation theory (EDT; Oliver 1977, 1980), focusing in particular on how and why user reactions change over time. Bhattacherjee (2001) and Bhattacherjee and Premkumar (2004) integrated the widely employed technology acceptance model (TAM; Davis et al. 1989) and EDT to understand intentions over time.

While rich insights have emerged from EDT as a theoretical lens, we attempt to remedy some of the methodological and analytical limitations of EDT work to date to further our understanding of technology adoption. First, EDT research in IS has used *direct measurement* of confirmation (or disconfirmation) rather than separately measuring the components (expectation and experience with technology use). Direct measurement distorts the joint effects of individual component measures on various outcomes (see Irving and Meyer 1994, 1995, 1999). Second, prior technology acceptance research in general and EDT research in IS in particular is limited to *linear models*. Linear models fail to reveal complexities that are anticipated in theories of congruence, such as EDT in which attitudes and behaviors result from the congruence between expectations and experiences (Edwards 1994, 2002). For example, one of the most influential studies relating person–environment fit to strain (French et al. 1982) had methodological and analytical problems resulting from the use of linear models that led to oversimplifying the complexity of the joint effect of the person and environment on strain. Edwards and Harrison (1993) remedied these problems by using polynomial modeling and response surface methodology. It is thus important to build upon and extend EDT research in IS with the more recent methodological and analytical approaches that do not suffer from these limitations.

Against this backdrop, the current work has the following objectives:

- to discuss the methodological and analytical limitations in prior EDT research in IS, and present polynomial modeling and response surface methodology as solutions
- to develop a polynomial model of expectation–disconfirmation in IS
- to empirically validate the proposed model

Theoretical Background

In this section, we discuss the two key theoretical perspectives that have been used to understand the changes in user reactions over time, TAM and EDT. Our work builds on prior EDT research in IS that used TAM as a foundation (e.g., Bhattacherjee 2001; Bhattacherjee and Premkumar 2004).

Technology Acceptance Model (TAM)

The technology acceptance model (Davis et al. 1989), shown in Figure 1, has been widely used to predict user acceptance of technology based on user perceptions of usefulness, ease of use, and attitude. Perceived usefulness is defined as the degree to which an individual thinks that using a particular system would enhance his or her job performance, and perceived ease of use is defined as the degree to which an individual thinks that using a particular system would be free of effort (Davis et al. 1989). Attitude is defined as an individual's positive or negative feeling about performing the target behavior (Davis et al. 1989; Taylor and Todd 1995). TAM theorizes that user perceptions of usefulness and ease of use of a target system determine the user's behavioral intention to use the system. Behavioral intention is a predictor of system use (Davis et al. 1989; Venkatesh et al. 2003). TAM also suggests that the effects of external variables, such as training and system design characteristics, on behavioral intention and use are mediated by the two key beliefs: perceived usefulness and perceived ease of use (Davis et al. 1989). Perceived usefulness is expected to be influenced by perceived ease of use because, other things being equal, the easier it is to use a system, the more useful it can be. Also, the direct effect of perceived ease of use on behavioral intention is significant only in the early stages of use (see Venkatesh et al. 2003). Over the long term, as user experience increases, this effect becomes indirect and operates through perceived usefulness (Venkatesh and Davis 2000; Venkatesh and Morris 2000).

Expectation–Disconfirmation Theory (EDT)

EDT has roots in marketing and consumer behavior research (Oliver 1977, 1980; Oliver and Desarbo 1988). EDT posits

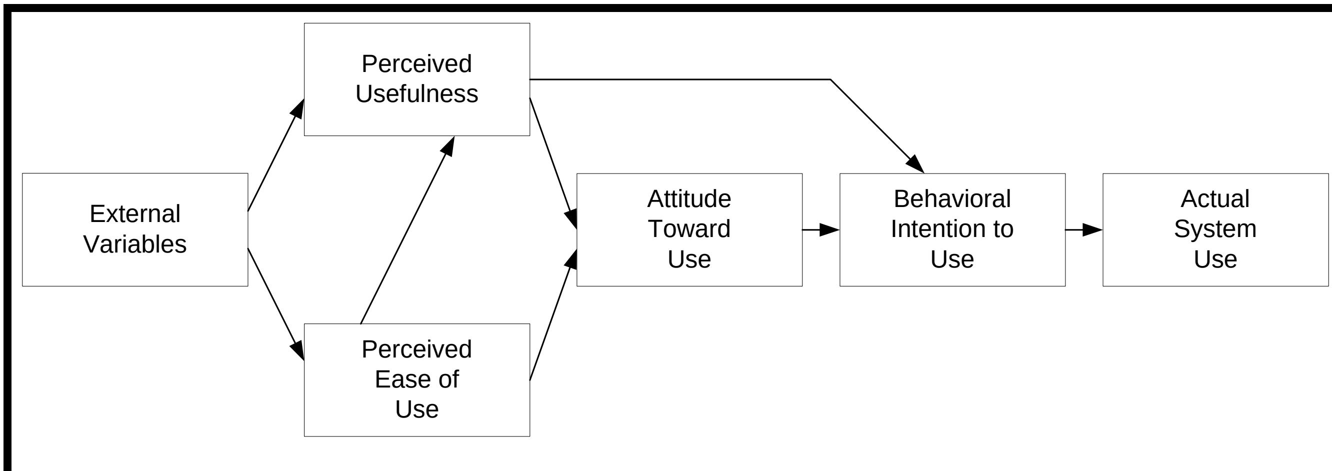

Figure 1. Technology Acceptance Model

that satisfaction is a function of prior expectations and disconfirmation (Oliver 1980; Susarla et al. 2003), and satisfaction is a key determinant of repurchase intentions (Oliver 1980; Oliver et al. 1994). Expectation is defined as a set of pre-exposure beliefs about the product (Olson and Dover 1979; Susarla et al. 2003). Disconfirmation is the discrepancy between expectations and actual experiences. Better-than-expected outcomes lead to positive disconfirmation and worse-than-expected outcomes lead to negative disconfirmation (Churchill and Surprenant 1982; Kopalle and Lehmann 2001; Oliver 1980; Oliver et al. 1994). The causal flow is as follows: (1) exposure to information about a product's performance characteristics leads to the formation of product-specific beliefs or expectations of the consumer (Olson and Dover 1979); (2) a cognitive comparison between expectations and actual experiences leads to a subjective calculation of disconfirmation (Oliver et al. 1994); and (3) a combination of expectations and disconfirmation determines the satisfaction level that, in turn, influences repurchase intentions.

EDT has been applied in many fields, including marketing and consumer behavior (e.g., Kopalle and Lehmann 2001; Szymanski and Henard 2001), service quality (e.g., Cronin and Taylor 1994; Kettinger and Lee 2005), psychology (e.g., Phillips and Baumgartner 2002), leisure behavior (e.g., Madrigal 1995), medicine (e.g., Baron-Epel et al. 2001; Joyce and Piper 1998), and human resources (e.g., Hom et al. 1998, 1999; Korman and Wittig-Berman 1981). A common theme in the expectation–disconfirmation literature is that satisfaction is a function of the size and direction of disconfirmation: the consumers are satisfied in the case of positive disconfirmation and dissatisfied in the case of negative disconfirmation. Further, fluctuation in satisfaction is higher as the degree of disconfirmation increases. Initially, Oliver (1980) hypothesized that prior expectation and disconfirmation are the only determinants of satisfaction, but subsequent research by Churchill and Surprenant (1982) showed that actual performance (i.e., experience) exerts independent effects on satisfaction beyond its impact via disconfirmation and, in some cases, experience is the only determinant of satisfaction (Brown et al. 2008).

In the IS literature, Ginzberg (1981) examined the impact of unrealistically high user expectations on system satisfaction and found that users who held realistic pre-implementation expectations were more satisfied with the system than users with unrealistic pre-implementation expectations. Szajna and Scamell (1993) used cognitive dissonance theory as a theoretical basis to show that users will change their level of satisfaction with a system to be more in line with the expectations. Staples et al. (2002) used EDT as a theoretical basis to argue that unrealistically high expectations will result in a lower level of perceived benefit when compared to realistic expectations. Incorporating EDT in the widely used TAM, Bhattacherjee (2001) identified the motivations underlying continuance intention (i.e., intentions to continue to use a system) and how these motivations influence continuance intention. Figure 2 shows the causal flow of EDT (Bhattacherjee 2001). Building on that work, Bhattacherjee and Premkumar (2004) explained how and why the beliefs and attitudes toward IT use change over time as users gain experience with the target system. In line with EDT, the results of these two studies show that the satisfaction with IS use is the strongest predictor of continuance intention. They further highlight the role of disconfirmation and satisfaction in driving the change in attitudes and beliefs over time.

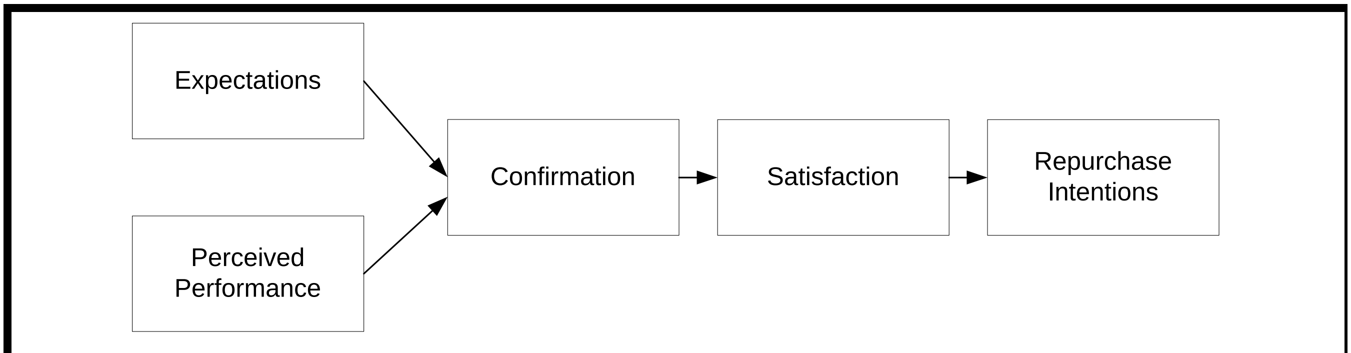

Figure 2. Expectation–Disconfirmation Theory

Gaps in Prior Expectation–Disconfirmation Theory Research in Information Systems

The introduction of EDT in technology adoption research was a key step in furthering our understanding of continued IS use (Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Brown et al. 2008). However, the methodological and analytical approach used in that work has two key limitations. Drawing on extant research in organizational behavior, we discuss these two limitations: direct measurement and linear models.

Direct Measurement

Irving and Meyer (1994, 1995, 1999) noted some concerns in using direct measurement of met expectations. The basic met expectation hypothesis is that the discrepancy between an individual's actual experiences on the job and the expectations prior to entering the organization determines their propensity to quit (Irving and Meyer 1995; Porter and Steers 1973). In essence, in an IS context, met expectations would suggest that the level of disconfirmation between a user's expectation of a system and the actual experience with using the system would determine continued system use intentions. In order to determine disconfirmation, two approaches are common: (1) measure expectation, measure experience, and compute the algebraic, arithmetic, or absolute difference score; or (2) measure disconfirmation directly. Both of these approaches reduce the component measures (i.e., pre-exposure expectations and post-exposure experience) to a single number.

The first approach of calculating difference scores has three key problems:

(1) Difference scores provide ambiguous and confounding results because one does not know whether the outcome variable is associated with both the component measures or one of the component measures (Edwards 1994; Lambert et al. 2003).

(2) Difference scores cause an oversimplification of the results as the three-dimensional relationship between the two component measures (expectation and experience) and the outcome variable is reduced to a two-dimensional relationship (Edwards 2002; Edwards and Parry 1993).

(3) Difference scores impose untested constraints on the congruence equations (Edwards and Harrison 1993).

In an attempt to avoid these problems associated with difference scores, a number of met expectations studies used the second approach, direct measurement of disconfirmation (see Irving and Meyer 1995). For example, Wanous et al. (1992) used direct measurement of met expectations to show significant correlations between employee attitudes and turnover intentions. Such direct measurement requires individuals to perform a mental comparison of the pre-exposure expectation with post-exposure experience that induces three methodological problems, which we discuss next.

First, as the direct measurement involves a mental comparison of component measures (e.g., pre-exposure expectation and post-exposure experience), it is possible that individuals may calculate a mental difference between their expectation and experience (Irving and Meyer 1995). This mental difference calculation makes direct measurement susceptible to the problems inherent in difference scores (Irving and Meyer 1995, 1999). Further, it has been argued that the two component measures used to determine the outcome measure are completely different constructs and this distinction between the constructs should be maintained throughout the data analysis (Edwards 2001, 2002). Combining two different constructs into one single score, say through a focus of disconfirmation, would produce ambiguous results (Edwards and Harrison 1993). Moreover, using direct measurement, as in the case of difference scores, reduces the three-dimensional relationship between the component measures and the outcome measure to a point in a two-dimensional relationship between the direct measure and the outcome measure. This results in an oversimplification of the joint effects of the component measures on the outcome measure (Edwards and Harrison 1993; Edwards and Parry 1993).

Second, in order to report subjective perceptions of disconfirmation by comparing pre-exposure expectations with post-exposure experiences, individuals are required to recall pre-exposure expectations. After gaining first-hand experience with the system for a considerable amount of time, if the individuals are unable to recall their pre-exposure expectations, these disconfirmation perceptions may suffer from a substantial recall bias as the present experience is far more salient and available compared to the original expectation (Karahanna et al. 1999; Ross 1989; Staples et al. 2002). Individuals recall historical attitudes by asking themselves how different they felt in the past compared to the present. Such recalled beliefs may be ambiguous and misinterpreted because memories consistent with people's beliefs are more accessible than the memories inconsistent with their beliefs. Also, recollection might lead to a misinterpretation of prior beliefs as supportive beliefs (Karahanna et al. 1999; Ross 1989). If individuals cannot recall past beliefs, they may guess, and such a guess will also be guided by the present experience (Ross 1989). This leads to a bias toward post-exposure beliefs, thus causing inaccurate results (see Irving and Meyer 1995).

Third, direct measurement does not capture the absolute levels of the component measures and the direction of the disconfirmation. Edwards and Parry (1993) found that boredom at the job would be low when both actual and desired job complexity are high rather than when both are low. As direct measurement of disconfirmation would measure only the difference between the expectation and the experience, absolute levels are disregarded. Therefore, the important distinctions between satisfaction levels for both high and low levels of pre-exposure expectations and post-exposure experiences are concealed. Further, direct measurement of disconfirmation leads to a unidirectional measure that makes no distinction between positive and negative disconfirmation. Thus, direct measurement of disconfirmation fails to encompass situations where post-exposure experiences exceed pre-exposure expectations.

There are several examples in psychology, organizational behavior, and human resources research where the use of direct measurement and/or difference scores has been challenged, and polynomial modeling and response surface methodology have helped shed new light on the underlying phenomenon (e.g., Edwards and Harrison 1993; Lambert et al. 2003). For example, in the personnel psychology literature, traditional studies of psychological contracts used either difference scores or a direct-measures approach to assess changes in satisfaction due to psychological contract breaches (e.g., Coyle-Shapiro and Kessler 2000; Kickul et al. 2002; Robinson and Morrison 2000). Using a methodological approach that did not suffer from shortcomings of either difference scores or direct measurement, Lambert et al. (2003) offered new insights into psychological contracts. They maintained a distinction between expectation and experience component measures by not combining them into a single score. The results of their investigation revealed important aspects of psychological contracts that were obscured in prior research. They showed that the effects of breach and fulfillment of a contract varied according to whether the breach signified deficiency or excess (direction of disconfirmation) and whether fulfillment was at high or low levels (absolute value of component measures).

Linear Models

As mentioned earlier, EDT proposes that the interaction between pre-exposure expectation and post-exposure experience determines disconfirmation. Much of the empirical research in technology acceptance literature (e.g., Bhattacherjee and Premkumar 2004; Davis et al. 1989) has used only linear models; such linear models assume that there is a similar effect for expectation and experience on disconfirmation. Therefore, even if the actual relationship between the component measures and the outcome measure is curvilinear, linear models would oversimplify the relationship and mask the true relationships among the variables (Edwards 2002; Edwards and Cooper 1990). There is a great awareness in the organizational behavior literature regarding the simplicity of linear models. Wanous et al. (1992) emphasized that confirmation of pre-entry expectations of employees had a strong effect on employee work attitudes. However, Irving and Meyer (1994) found that it is more important to improve positive work experiences than to meet expectations in order to improve work attitudes. They found significant curvilinear relationships between responsibility-related experiences and work adjustment indexes that indicated that responsibility-related experiences contributed positively to work adjustment up to a certain point, after which a negative relationship was observed. Therefore, complex congruence hypotheses using curvilinear effects are required to test the full range of both the component measures of pre-exposure expectations and post-exposure experiences (see Edwards 1996; Edwards and Harrison 1993).

Methodological and Analytical Advances

Drawing on the vast body of research in the organizational behavior literature, we present polynomial modeling and response surface methodology as approaches that can help advance our understanding of EDT in IS by addressing the limitations presented in the preceding sections. Polynomial modeling and response surface methodology have been used widely in organization behavior (e.g., Hecht and Allen 2005; Kristof 1996), marketing (e.g., Kim and Hsieh 2003), and personnel psychology (e.g., Shaw and Gupta 2004). We present the basic ideas of the two approaches and how these approaches address the limitations discussed earlier.

Polynomial Modeling

Polynomial modeling permits the examination of complex relationships between component measures and an outcome variable. Based on a basic theoretical model, Z = f (X, Y), this technique allows the examination of curvilinear terms so that a more accurate picture of the relationship between component measures and an outcome variable can be detected (Edwards 1994, 2002; Edwards and Harrison 1993). Polynomial modeling involves a hierarchical analysis of polynomial equations. For example, a quadratic polynomial equation is

$$Z = b_0 + b_1 X + b_2 Y + b_3 X^2 + b_4 XY + b_5 Y^2 + e \qquad (1)$$

In the first stage of the hierarchical analysis, component scores for X and Y are entered to test their linear relationship with Z. During the second stage of analysis, higher-order terms (X^2 and Y^2) are added into the equation along with the product term (XY) to test for the presence of curvilinear (here, quadratic) relationships. Subsequently, cubic terms could be added into the equation in order to test for the presence of further higher-order curvatures (for a detailed discussion, see Edwards 2002; Edwards and Harrison 1993). This hierarchical analysis continues until the variance explained by the next higher-order equation is not statistically significant. As noted earlier, measurement of disconfirmation involves comparing two distinct component measures: pre-exposure expectation and post-exposure experience. The three-dimensional analysis facilitated by polynomial modeling allows us to maintain this distinction throughout the analysis and test complex congruence hypotheses, such as the difference in the absolute level of disconfirmation when the values of both expectations and experiences are high rather than when both are low, a distinction that is not possible to assess using direct measures. Although such analysis certainly can be performed using a linear model that incorporates component measures, the central contribution is the testing of higher-order (i.e., curvilinear) effects. This technique is illustrated in Edwards and Harrison (1993), who reanalyzed one of the most widely accepted person-environment theories (French et al. 1982) and found that many of the relationships were either *ambiguous* or *substantially more complex.*

Response Surface Methodology

Response surface methodology is a set of visual and statistical tests that provide a rich and deep understanding of the intricacies of polynomial models. Equations in polynomial models often yield patterns of coefficients that are difficult to interpret. Response surface methodology is used as an interpretive technique to show how these coefficients describe the surfaces they imply (for a detailed discussion, see Edwards 2002; Edwards and Parry 1993). Further, statistical tests allow us to better understand and establish the contours and details of the plotted surface. Response surface methodology focuses on three main features of the surfaces generated from polynomial models: stationary point, principal axes, and slopes along various lines of interest. A stationary point is defined as a point at which the slope of a surface is zero in all directions (Edwards and Parry 1993). Principal axes run perpendicular to each other and intersect at the stationary point (Edwards and Parry 1993). For a convex surface, the upward curvature is greatest along the first principal axis and least along the second principal axis. For a concave surface, the downward curvature is least along the first principal axis and greatest along the second principal axis. The other lines of interest in response surface methodology are the confirmation axis, which is the axis along which both the component measures are equal (X = Y), and the disconfirmation axis, which is the axis perpendicular to the confirmation axis (Edwards and Parry 1993).

When coupled with response surface methodology, polynomial modeling goes beyond testing the relationships represented by fit (direct) measures because constraints imposed by these measures can be relaxed and higher-order terms representing inflections and curvatures can be included (Edwards 2001). For example, in their study, French et al. (1982) concluded that actual and desired quantitative work load had symmetric relationships with job satisfaction. In contrast, Edwards and Parry (1993), using polynomial modeling coupled with response surface analysis, indicated that actual and desired quantitative work load had an asymmetric relationship with job satisfaction.

Theory

We examine EDT research in IS to clarify the roles of beliefs, attitudes, and disconfirmation in determining intention. In prior EDT research in IS, behavioral intention in the sustained use stage was determined by post-exposure usefulness and attitude toward technology use (Bhattacherjee and Premkumar 2004). A comparison of pre-exposure usefulness and attitude with those of post-exposure usefulness and attitude results in disconfirmation that influences behavioral intention to continue using the system. Pre-exposure usefulness (U_1) and attitude (A_1) relate to the acceptance stage, and post-exposure usefulness (U_2) and attitude (A_2) relate to the sustained (continued) use stage. Building on Oliver et al.'s (1994) discussion of the causal flow in EDT that we discussed earlier, Bhattacherjee (2001) describes the causal flow of EDT in IS as follows:

(1) Training on a new technology in the early stages of exposure lead to a user's formation of usefulness perceptions and attitude related to using the system.

(2) Over time, as a user gains experience with the system, his or her usefulness perceptions and attitude are modified.

(3) A cognitive comparison between usefulness and attitude in the pre-exposure and post-exposure stages leads to a user's subjective calculation of disconfirmation.

(4) The usefulness and attitude, along with the disconfirmation level, influence a user's behavioral intention to continue using the system.

The pre-exposure belief is formed mostly based on third-party information (Olson and Dover 1979) whereas the post-exposure belief is formed mostly based on first-hand experience with the system (Oliver 1980). According to TAM, only the effect of perceived usefulness is significant in the sustained use (post-exposure) stage because, as the user gains experience with the technology, the effect of perceived ease of use becomes indirect and operates through perceived usefulness (see Venkatesh et al. 2003). Consistent with TAM, we expect perceived usefulness to be a strong predictor of behavioral intention in the post-exposure stage.

The theory of planned behavior (Ajzen 1991) suggests that behavioral intention to perform a behavior is predicted by attitude toward the behavior. Recent developments in the technology adoption literature have found that, in the presence of perceived usefulness and ease of use in the model, the relationship between attitude and behavioral intention is not significant (see Venkatesh et al. 2003). However, EDT research in IS (Bhattacherjee and Premkumar 2004) has used attitude and usefulness as simultaneous predictors of behavioral intention. To faithfully replicate and go beyond prior EDT research in IS, we examine behavioral intention as a function of attitude in the pre-exposure (A_1) and post-exposure (A_2) stages along with their higher-order terms. While prior EDT research in IS has used satisfaction as a predictor of attitude, we focus only on the direct predictors of behavioral intention, namely, perceived usefulness and attitude.

As mentioned earlier, prior EDT research in IS used direct measurement of disconfirmation. In contrast, we preserve the distinction between the perceived usefulness component measures (U_1 and U_2) and attitude component measures (A_1 and A_2) by examining behavioral intention as a function of these component measures and their higher-order terms. Such polynomial models would allow us to examine the effect of the interaction (disconfirmation) between the component measures, along with their individual effects, on behavioral intention while avoiding the methodological and analytical problems discussed earlier. Further, higher-order terms included in the polynomial models would allow us to represent additional inflections and curvatures in the underlying surfaces and test such complex relationships. The theoretical rationale driving these curvilinear relationships is presented next.

Hypothesis Development

We primarily draw from cognitive dissonance theory (Festinger 1957) to develop our hypotheses. Cognitive dissonance theory posits that a state of psychological discomfort is caused by an inconsistency among a person's beliefs, attitudes, and/or actions. The degree of psychological discomfort varies in intensity based on the importance of issue and the degree of inconsistency (Festinger 1957; Szajna and Scamell 1993). This psychological discomfort induces a dissonance reduction strategy by changing beliefs, attitudes, or behaviors to be more consistent (Carlsmith and Aronson 1963; Elliot and Devine 1994; Festinger 1957; Szajna and Scamell 1993).

Aronson and Carlsmith (1962) argued that behavior inconsistent with a self-relevant expectancy should arouse dissonance.

Moreover, dissonance would be aroused whether the self concept involved is positive or negative. Specifically, a person experiences dissonance if he or she expects a certain event and the event does not occur. The individual's cognition, that he or she expects the event to occur, is dissonant with the cognition that the event did not occur (see also Carlsmith and Aronson 1963). If dissonance arises from the disconfirmation of expectancy, then it would result in a negative state (Elliot and Devine 1994). In an experiment, Carlsmith and Aronson (1963) gave participants a random sequence of sweet and bitter solutions to taste. On the basis of certain signals given by the experimenter, participants developed certain expectancies that the next solution they would taste is likely to be bitter or sweet. When the expectations of the participants were disconfirmed due to incorrect signals, the solutions were judged to taste more unpleasant. A bitter solution was rated as being more bitter and a sweet solution was rated as being less sweet. Carlsmith and Aronson explained the opposite direction of the results for bitter and sweet as an affective response to the psychological discomfort of the inconsistency. This suggests that individuals are averse to being wrong and have negative emotional response to disconfirmation, whether the surprise is pleasant or unpleasant (see also Hogan 1987). Therefore, prior expectations would interact with experiences to lower evaluations. Specifically, even though pleasant experiences should intuitively only increase individual evaluations, positive disconfirmation decreases this positive effect. Also, negative disconfirmation would increase the negative effect.

Cooper and Fazio (1984) found that expectation disconfirmation does not have any proximal role in dissonance reduction. It only serves as the instigator of the attributional interpretation. It is the psychological discomfort aroused by the psychological judgment that drives the dissonance reduction (Elliot and Devine 1994). In the present study, the state of disconfirmation arises when pre-exposure usefulness (or attitude) is inconsistent with the post-exposure usefulness (or attitude). Users experience positive disconfirmation when post-exposure usefulness (or attitude) exceeds pre-exposure usefulness (or attitude) and negative disconfirmation when pre-exposure usefulness (or attitude) exceeds post-exposure usefulness (or attitude). Both positive and negative disconfirmation result in a state of dissonance resulting in psychological discomfort to the users of the system. This psychological discomfort would cause the users of the system to implement a dissonance reduction strategy resulting in a negative effect on their behavioral intention to continue using a system. In the case of positive disconfirmation, users experience a "pleasant surprise" (Lattin and Bucklin 1989; Rust and Oliver 2000) that can be expected to mitigate some of the negative consequences of the dissonance/disconfirmation. In contrast, in the case of negative disconfirmation, there will be no such mitigating effect. Therefore, we hypothesize

> *H1a: Positive disconfirmation would negatively influence behavioral intention to continue using a system.*

> *H1b: Negative disconfirmation would negatively influence behavioral intention to continue using a system.*

> *H1c: Negative disconfirmation would have a stronger negative effect on behavioral intention to continue using a system when compared to the negative effect that positive disconfirmation would have.*

As the degree of disconfirmation increases, the negative effect on behavioral intention to continue using a system becomes stronger and follows a curvilinear fashion. We draw from the ideas in prospect theory in justifying our hypotheses (see Kahneman and Tversky 1979; Tversky and Kahneman 1981). Prospect theory posits that the value function of losses is steeper than that of gains. This basic idea has been applied in IS research contexts, for example, in relation to project escalation (see Keil et al. 2000). Therefore, as the prospect of a loss increases, the likelihood of the negative outcome is also likely to increase. Following this logic, we expect that, as the intensity of dissonance increases, the negative effect on behavioral intention becomes stronger. Further, a state of confirmation is achieved when there is consistency between pre-exposure and post-exposure usefulness (or attitude). In such a state, users do not experience any dissonance and, therefore, users do not experience any psychological discomfort (Elliot and Devine 1994; Szajna and Scamell 1993). In such a state, there will be no adverse effect on behavioral intention to continue using a system. With the increase in intensity of dissonance, the psychological discomfort perceived by an individual is likely to become stronger because inconsistency among a person's beliefs, attitudes, and/or actions increases. This would further enhance the adverse effects of positive and negative disconfirmation on behavioral intention. Specifically, behavioral intention to continue using a system decreases at a faster rate as the variation between pre-exposure and post-exposure usefulness (or attitude) increases. Therefore, we expect that

> *H2a: Behavioral intention decreases at a faster rate as the post-exposure usefulness* (or attitude) *increases and pre-exposure usefulness* (or attitude) *decreases.*

H2b: Behavioral intention decreases at a faster rate as the pre-exposure usefulness (or attitude) *increases and post-exposure usefulness* (or attitude) *decreases.*

Analytical Representation of the Hypotheses

In order to test the hypotheses presented in this research, it is important to convert these hypotheses into statistical tests that can be examined using polynomial modeling coupled with response surface methodology. We can accomplish such an examination based on a test of the quadratic model. We first explain the basic quadratic equation, and then provide specific mapping between hypotheses and equations, along with statistical tests. The general form of a quadratic equation for predicting behavioral intention using usefulness is

$$BI = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + e \quad (3)$$

Where, BI represents behavioral intention to continue using a system; U_1 represents pre-exposure usefulness; and U_2 represents post-exposure usefulness.

Edwards and Parry (1993) show that the coordinates of the stationary point (X_0 Y_0; the point at which slope of the surface is zero in all directions) are

$$X_0 = (b_2b_4) - (2\ b_1b_5) / (4\ b_3b_5) - b_4^2 \quad (4)$$

$$Y_0 = (b_1b_4) - (2\ b_2b_3) / (4\ b_3b_5) - b_4^2 \quad (5)$$

These coordinates for the stationary point are used to develop the equations for first and second principal axes. Edwards and Parry show that the equation for the first principal axis (line along which the slope of a concave surface is minimum) is given by

$$Y = p_{10} + p_{11} X_0 \quad (6)$$

where

$$p_{11} = (b_5 - b_3 + \text{sqrt}\ ((b_3 - b_5)^2 + b_4^2)) / b_4 \quad (7)$$

$$p_{10} = Y_0 - p_{11} X_0 \quad (8)$$

Further, according to Edwards and Parry, the equation for the second principal axis (the line along which the slope of a concave surface is maximum) is given by

$$Y = p_{20} + p_{21} X_0 \quad (9)$$

where

$$p_{21} = (b_5 - b_3 - \text{sqrt}\ ((b_3 - b_5)^2 + b_4^2)) / b_4 \quad (10)$$

$$p_{20} = Y_0 - p_{21} X_0 \quad (11)$$

H1a and H1b state that both positive and negative disconfirmation would have a negative effect on behavioral intention. Therefore, the slope of the response surface decreases as the post-exposure usefulness (or attitude) deviates from the pre-exposure usefulness (or attitude) in either direction. In other words, in the region where the post-exposure usefulness (or attitude) is higher than the pre-exposure usefulness (or attitude), that is, the positive disconfirmation, the slope of the response surface is positive; and in the region where post-exposure usefulness (or attitude) is lower than the pre-exposure usefulness (or attitude), that is, the negative disconfirmation, the slope of the response surface is negative. Because the slope of the surface changes from positive to negative along the disconfirmation axis, the maximum curvilinear slope is along the disconfirmation axis ($X = -Y$) or the second principal axis of the response surface runs along the disconfirmation axis. The second principal axis would be parallel to the disconfirmation axis if it makes an angle of -45° with the XY plane or its slope is -1. Therefore, these hypotheses will be supported if

> *Test #1:* The value of p_{21}, which represents the slope of the disconfirmation axis, in equation (9) is significant; and
>
> *Test #2:* The value of p_{21} is not significantly different from -1.

H1c states that behavioral intention for positive disconfirmation is higher than behavioral intention for negative disconfirmation. Therefore, the linear slope of the disconfirmation axis should be significant and positive. This hypothesis will be supported if

> *Test #3:* The quantity ($b_1 - b_2$), which represents the linear slope of the disconfirmation axis, is significant; and
>
> *Test #4:* The quantity ($b_1 - b_2$), which represents the linear slope of the disconfirmation axis, is positive.

H2a and H2b indicate that the negative effect of disconfirmation increases as the degree of disconfirmation increases. Because of this effect, the slope of the response surface for both positive as well as negative disconfirmation would be curvilinear such that as the degree of disconfirmation increases, the slope of the response surface along the disconfirmation axis increases. This increasing slope would be represented by the curvilinear (quadratic) slope of the disconfirmation axis. Therefore, to support these hypotheses (H2a and H2b), the quadratic slope should be significant. This hypothesis will be supported if

> *Test #5:* The quantity ($b_3 - b_4 + b_5$), which represents the quadratic slope of the disconfirmation axis, is significant.

H1a and H2b implicitly suggest that the maximum value of the behavioral intention would be observed when users do not experience any disconfirmation. Therefore, the slope of the response surface would be minimum along the confirmation axis—that is, line along which pre-exposure usefulness (or attitude) equals post-exposure usefulness (or attitude)—or the first principal axis runs along the confirmation axis. The first principal axis would be parallel to the confirmation axis if this line makes an angle of 45^o with the XY plane or if the slope of the first principal axis is 1. Therefore, these hypotheses will be supported if

> *Test #6:* The value of p_{11}, which represents the slope of the confirmation axis, in equation (6) is not significantly different from 1.

Moreover, the overall shape of the response surface is concave because all of these hypotheses collectively suggest that the response surface for both usefulness (or attitude) would be curvilinear such that surface takes on a positive slope in the region of positive disconfirmation and a negative slope in the region of negative disconfirmation with the change in slope occurring along the confirmation axis. The concave shape exists if

> *Test #7:* The sign of ($b_3 - b_4 + b_5$), quadratic slope along the disconfirmation axis, is negative.

Method

The purpose of this study was to examine the effect of usefulness and attitude in the pre-exposure and post-exposure stages on the behavioral intention to continue using a system. In this section, we discuss the setting, participants, data collection, and measurement.

Setting, Participants, and Data Collection

The setting for the study was an organization in which all of the employees were in the process of being introduced to a new technology. The system introduced was an internal electronic human resource information system that provided forms and policies online, provided current tax information (including W-2 access), benefits information (e.g., general information and employee-specific information about insurance, retirement, stock, etc.), transactional information (e.g., reimbursement status), leave application and status, etc. The system was to provide employees with one-stop, web-based access to all information related to human resources on the organization's intranet. Previously available options (paper-based or other fragmented systems) continued to be available for the entire duration of our study, thus rendering the use of this system to be voluntary.

The sampling frame, a list of all employees of the organization, comprised 2,500 employees. While all 2,500 employees were contacted, 1,143 employees provided completed, usable responses at both points of measurement, resulting in an overall response rate of about 45 percent. Of the 1,143 responses, 469 were women (approximately 41 percent). The average age of the respondent was 36.1 years (SD = 9.1). On average, respondents had 7.6 years of prior computer experience (SD = 3.4). The demographic profile of the respondents matched the profile of the sampling frame, thus alleviating concerns about nonresponse bias.

Measurements were taken immediately after the completion of the training program regarding the new technology and after the users gained experience with the technology. This approach is consistent with prior EDT, training, and individual adoption research in IS where individual reactions to the technology were studied (e.g., Bhattacherjee and Premkumar 2004; Davis et al. 1989; Venkatesh et al. 2003). The first measurement (t_1) of user perceptions was one week after the completion of initial training. The second measurement (t_2) was six months after the employees started using the technology. Measurement at time t_1 represents the expectations of the employees that are developed when they were presented with the new system in the training sessions. However, behavioral intention measured after the first week was not used in this paper. Measurement at time t_2 represented the post-exposure experiences when the users had gained substantial experience with the system and experienced changes, if any, in their usefulness perceptions, attitude, and intention. In addition to these user reactions, behavioral intention to continue using the system was measured at time t_2. The appendix provides a list of the items.

Measurement

Edwards (2002) suggested that commensurate measurement is required to ensure the conceptual relevance of the component measures to one another and to meaningfully interpret the results. Commensurate measurement means that the respondents express the components in terms of the same content dimensions. Examples of such commensurate measures include perceived and wanted work attributes, expected and received pay, and actual and desired challenge (Edwards 1994). In much of the polynomial modeling research using response surface methodology, only one set of constructs (e.g., expected pay and received pay) are examined as predictors in a single model so as to meaningfully interpret them graphically (see Edwards 1994; Edwards and Parry 1993; Lambert et al. 2003). Thus, a series of models with different sets of predictors were used to examine the same dependent variables—for example, Lambert et al. (2003) examined promised pay, delivered pay, and associated higher-order terms as predictors of satisfaction. They also examined promised recognition, delivered recognition, and associated higher-order terms as predictors of satisfaction. In keeping with this, we measured expectations of perceived usefulness, expectations of attitude, and behavioral intention separately. Also, we analyzed the perceived usefulness–behavioral intention and attitude–behavioral intention relationships separately.

A questionnaire was created with previously validated items. Perceived usefulness and attitude were measured using four-item scales adapted from prior EDT and technology adoption research (see Bhattacherjee and Premkumar 2004; Venkatesh et al. 2003). These scales have been adapted and used in a variety of settings (e.g., Adams et al. 1992; Koufaris 2002; Lim and Benbasat 2000; Taylor and Todd 1995; Venkatesh and Davis 2000). Behavioral intention to continue using the system was measured using a three-item scale adapted from Davis et al. (1989) that has been used extensively in prior research (see Venkatesh et al. 2008; Venkatesh et al. 2003). Seven-point scales were used for the measurement of all the constructs, with 1 being the negative end of the scale and 7 being the positive end of the scale. A Likert agreement scale was used for usefulness and intention while a semantic differential scale was used for attitude. The items were worded appropriately to measure pre-exposure expectations and post-exposure experiences.

Analysis

Like any other regression analysis, the polynomial regression analysis begins with a representation of the conceptual model as a regression equation (Edwards 2002). The constraints imposed by the direct measurement of disconfirmation in Bhattacherjee and Premkumar (2004) were relaxed using the procedure described by Edwards and Harrison (1993). A polynomial model is supported if the variance explained by higher-order terms is significant (Edwards 1994).

Prior to conducting the analysis, we screened the data set for outliers using Cook's D and standardized residuals from regression equations. We excluded cases that met the minimum criteria set by Bollen and Jackman (1990). The data at both points of measurement were scale centered by subtracting the midpoint of the scale from the measured value. Scale centering reduces multicollinearity between the component measures and their associated higher-order terms (Aiken and West 1991). As suggested by Podsakoff and Organ (1986), Harmon's one-factor test and the partial correlation procedure were also conducted to check for the problems associated with common method bias. All the variables of interest were entered into a factor analysis to check if (1) a single factor emerges from the factor analysis and (2) one single factor accounts for a majority of the covariance in interdependent and criterion variables. Neither of the two conditions was true. Further, the first factor from the unrotated factor matrix was entered into a linear regression model as a control variable to check if a meaningful relationship among the variables of interest exists even after the first factor was controlled. We found that this condition was indeed satisfied. Therefore, based on the results of these tests, we found that our sample did not suffer from the problems associated with common method bias.

We used a jackknifing procedure to estimate significance levels for stationary points and slopes along various axes. This procedure has been widely used in prior management research (e.g., Edwards and Parry 1993). Nonparametric procedures, such as jackknifing and bootstrapping, are used when traditional techniques, such as regression analyses, do not provide formulas for the estimation of specific expressions—here, standard errors and significance levels for stationary points and slopes (see Efron and Gong 1983). The jackknifing procedure involves dropping one observation from the sample and calculating the expression of interest (e.g., slope along principal axes). The excluded value is then replaced by another observation and this procedure continues until all the observations are dropped exactly once. Assessing the variation in the resulting values of expression of interest allows us to estimate the standard errors for that expression. These are then used to determine the significance levels. In this study, we used n-1 samples of n-1 observations (i.e., 1,142 samples of 1,142 observations) to determine the significance levels for stationary points and slopes along various axes. Bootstrapping is preferred over jackknifing if the number of samples from the dataset is small. However, the large number of samples used for the jackknifing procedure in the present study alleviates bias and efficiency concerns (Efron and Gong 1983).

Hierarchical regression analysis was used to estimate the polynomial models. In the first stage of the hierarchical analysis, the first-order equations were tested. Higher-order terms, including the interaction terms, were then added to the regression equation until there was no significant change in the R^2. The general forms of the equations are

First-order equation: $$Z = b_0 + b_1 X + b_2 Y + e \quad (12)$$

Second-order equation: $$Z = b_0 + b_1 X + b_2 Y + b_3 X^2 + b_4 XY + b_5 Y^2 + e \quad (13)$$

Response surfaces for perceived usefulness predicting behavioral intention and attitude predicting behavioral intention were plotted using the unconstrained polynomial equations with the highest value of R^2. Commensurate measures of usefulness and attitude in the post-exposure and pre-exposure stages were used as component measures on the X- and Y-axes, respectively, predicting behavioral intention on the Z-axis. Using the procedure described in Edwards and Parry (1993), the basic features of the response surfaces were examined: stationary point, principal axes, and slopes along lines interest—congruence (X = Y) and incongruence (X = -Y) axes.

Results

Table 1 presents the reliabilities, descriptive statistics, and correlations. Reliabilities of the scales were assessed using Cronbach's alpha and found to be greater than 0.90 in all cases. The means of all scales were above the midpoint of 4, with standard deviations being above 1. As expected, all constructs were correlated with each other, with the highest correlations being between usefulness and intention. Principal components analysis, with varimax rotation yielded a five-factor solution, as expected. Those results supported internal consistency, with all loadings being greater than 0.80, and discriminant validity with all cross-loadings being less than 0.30; the specific results are not shown here given the consistency with much prior technology adoption research (Bhattacherjee and Premkumar 2004; Venkatesh et al. 2003).

Confirmatory Polynomial Regression Analysis

Edwards (2002) suggests that, in order to perform confirmatory polynomial regression analysis, constraints imposed by the algebraic difference on the regression equation should be relaxed and this relaxed equation should then be tested to see if the constraints imposed are satisfied (see also Edwards and Harrison 1993). For example, a linear equation algebraic difference scores is given by

$$Z = b_0 + b_1(X - Y) + e \quad (14)$$

Expanding this equation would yield

$$Z = b_0 + b_1 X - b_1 Y + e \quad (15)$$

Equation with X and Y as separate predictors of Z is given by

$$Z = b_0 + b_1 X + b_2 Y + e \quad (16)$$

Comparing equations (15) and (16), we can see that the algebraic difference score impose constraints such that the coefficient of Y is required to be equal and opposite to the coefficient of X ($b_1 = -b_2$). Edwards (2002) further argues that the conceptual model is supported if (1) the variance explained by the unconstrained equation differs from zero; (2) the coefficients follow appropriate pattern (i.e., they are significant and in the right direction); (3) constraints imposed by the model are satisfied; and (4) the increase in variance explained by including higher-order terms in the unconstrained equation does not differ from zero.

Confirmatory polynomial regression analysis was used to test the EDT model as specified in Bhattacherjee and Premkumar (2004). The baseline EDT model presented by Bhattacherjee and Premkumar did not include the direct effect of disconfirmation on behavioral intention. Behavioral intention was measured as a function of only attitude and perceived usefulness. Therefore, the only constraint left to be tested in the conceptual model was the presence of higher-order (curvilinear) terms.

Table 2 shows the results of the constrained regression equation: $BI = f(U_2, A_2)$. Consistent with prior technology acceptance research (e.g., Venkatesh et al. 2003), perceived usefulness in the post-exposure stage was a strong predictor of behavioral intention. The unconstrained models for behavioral intention predicted by usefulness and attitude are presented in Tables 3 and 4 respectively. As the variance explained by the higher-order equation is significantly more than the variance explained by the linear EDT model, the linear model is rejected in favor of a curvilinear—here, quadratic—model (see Edwards 1994, 2002).

Exploratory Polynomial Regression Analysis

To further clarify the relationship between perceived usefulness, attitude, and behavioral intention, we conducted explor-

Table 1. Reliabilities, Descriptive Statistics, and Correlations

	Cronbach's Alpha	Mean	Std Dev	U_1	A_1	U_2	A_2
U_1	.94	4.55	1.22				
A_1	.92	4.51	1.30	.42***			
U_2	.92	4.05	1.11	.41***	.23***		
A_2	.91	4.43	1.08	.24***	.35***	.28***	
B_1	.92	4.32	1.20	.51***	.28***	.65***	.44***

Notes: U_1: Pre-exposure usefulness; A_1: Pre-exposure attitude; U_2: Post-exposure usefulness; A_2: Post-exposure attitude; BI: Behavior intention to use the system.
*p < .05; **p < .01; ***p < .001.

Table 2. Constrained Regression Equations for Prior EDT Research in IS

Dependent variable	Independent variables	R^2	β
Behavioral intention	Post-exposure usefulness (U_2)	.41	.61***
	Post-exposure attitude (A_2)		.29***

Note: *p < .05; **p < .01; ***p < .001

Table 3. Unconstrained Model: Predicting Behavioral Intention Using Usefulness

		First-Order Linear Equation		Second-Order Quadratic Equation	
Dependent variable	Independent variables	R^2	β	R^2	β
Behavioral intention	U_1	.40	.20***	.56	.10**
	U_2		.62***		.12**
	U_1^2				-.22***
	U_1U_2				.54***
	U_2^2				-.39***

Notes: U_1: Pre-exposure usefulness; U_2: Post-exposure usefulness.
*p < .05; **p < .01; ***p < .001.

Table 4. Unconstrained Model: Predicting Behavioral Intention Using Attitude

		First-Order Linear Equation		Second-Order Quadratic Equation	
Dependent Variable	Independent Variables	R^2	β	R^2	β
Behavioral intention	A_1	.17	-.08***	.20	-.13**
	A_2		.40***		.32***
	A_1^2				.05
	A_1A_2				.14**
	A_2^2				-.15**

Notes: A_1: Pre-exposure attitude; A_2: Post-exposure attitude.
*p < .05; **p < .01; ***p < .001.

atory analyses using polynomial modeling and response surface methodology (Edwards 2002; Edwards and Harrison 1993; Edwards and Parry 1993). The results of the exploratory analysis are also provided in Tables 3 and 4. The significant coefficients of the higher-order terms show that the perceived usefulness–behavioral intention (shown in Table 3) and attitude–behavioral intention (shown in Table 4) relationships are curvilinear. Also, the F-test shows that the R^2 of the second-order quadratic equation for usefulness (and attitude) predicting behavioral intention was significantly higher than the first-order linear equation.

The response surface of perceived usefulness predicting behavioral intention was concave, as shown in Figure 3. The stationary point (the point at which the slope of the surface is zero in all directions) for the surface was quite close to the origin (X_0 = -0.49, p < .01; Y_0 = -0.59, p < .01). The first principal axis (the line along which the slope of a concave surface is minimum) passed through the origin; the equation of the first principal axis is Y = -0.02 + 1.15 X. The slope of this surface along the confirmation axis was positive and showed linear (a_x = 0.46, p < .01) and quadratic (a_x^2 = 0.41, p < .01) components. Also, the first principal axis intersected the disconfirmation axis at the point X = 0.01, p < .01; Y = -0.01, p < .01, thus indicating that the lateral shift of the surface along the disconfirmation axis was negligible. The second principal axis (the line along which the slope of a concave surface is maximum) passed just to the left of the origin; the equation of the second principal axis is Y = -1.01 – 0.87 X. The slope of the surface along the disconfirmation axis was negative, and showed very small but significant linear (a_x = 0.02, p < .01) and significantly high quadratic (a_x^2 = -2.40, p < .01) components.

We observed that the slope of second principal axis was significant, providing support for H1a and H1b (test #1). Moreover, we found that there was no significant rotation of the surface along the disconfirmation axis because the slope of the second principal axis was not significantly different from -1 (p < .01; test #2). The linear slope of the response surface along the disconfirmation axis (quantity b_1 – b_2), although significant and positive, is negligible, thus providing very limited support for H1c (test #3 and test #4). The quadratic slope along the disconfirmation axis (quantity $b_3 - b_4 + b_5$) is significant and high, thus providing strong support for H2a and H2b (test #5). We also found that the slope of the first principal axis was not significantly different from 1. This confirms that the first principal axis runs parallel to the confirmation axis and provides further support to H1a and H1b (test #6). Of particular interest from the perspective of this research is that a state of confirmation was found to result in a higher level of behavioral intention than did a state of disconfirmation. For a concave surface with negligible rotation and lateral shift, the maximum value of the outcome variable is observed at the line of perfect fit (Edwards and Parry 1993). Therefore, the maximum value of behavioral intention was along the confirmation axis. Also, the sign of the slope of the response surface along the disconfirmation axis (quantity $b_3 - b_4 + b_5$) was negative. The strong negative quadratic slope indicated that the surface along the disconfirmation axis was strongly concave, thus further supporting H1a and H1b (test #7).

In combination, these results indicated five key effects. First, behavioral intention decreased as post-exposure usefulness deviated from the pre-exposure usefulness in either direction. Therefore, positive as well as negative disconfirmation negatively influenced behavioral intention. Second, the negative influence of disconfirmation became stronger as the degree of disconfirmation increased. Third, as the surface had an overall positive slope along the confirmation axis, behavioral intention was higher when pre-exposure and post-exposure usefulness were both high than when both were low. Fourth, the slight convex nature of the surface along the confirmation axis indicated that behavioral intention was lowest along the confirmation axis when both pre-exposure and post-exposure usefulness were moderate (at the center) and increased in both directions. Fifth, the negative influence on behavioral intention was similar for negative disconfirmation and positive disconfirmation.

The response surface for attitude predicting behavioral intention was somewhat similar to the response surface for perceived usefulness predicting behavioral intention, as shown in Figure 4. The stationary point for the surface was fairly close to the origin of the X-axis and the Y-axis (X_0 = 1.19, p < .01; Y_0 = -1.07, p < .01). The first principal axis did not pass through the origin; the equation of the first principal axis was Y = -3.22 + 1.81 X. The slope of this surface along the confirmation axis was positive, and showed linear (a_x = 0.11, p < .001) and quadratic (a_x^2 = 0.03, p < .001) components. Also the first principal axis intersected the disconfirmation axis at the point X = 1.14, p < .01; Y_0 = -1.14, p < .01, thus indicating that the surface had a slight lateral shift in the area where post-exposure attitude was higher than pre-exposure attitude. The second principal axis almost passed through the origin; the equation of second principal axis is Y = -0.41 – 0.55 X. The slope of the surface along the disconfirmation axis was negative and showed significant linear (a_x = 0.29, p < .01) and quadratic (a_x^2 = -0.13, p < .01) components.

In this response surface, we observed that the slope of the second principal axis was significant, providing support for

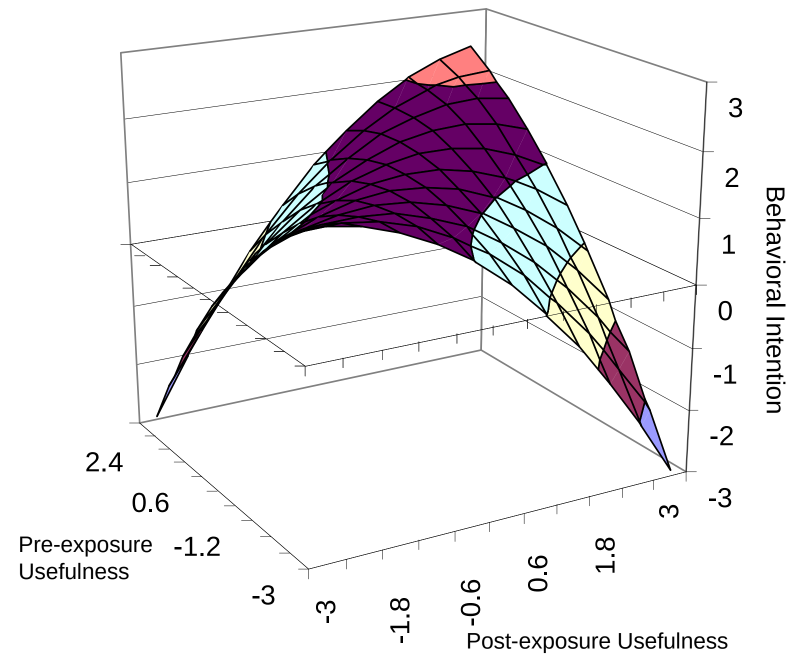

Figure 3. Response Surface for Perceived Usefulness Predicting Behavioral Intention

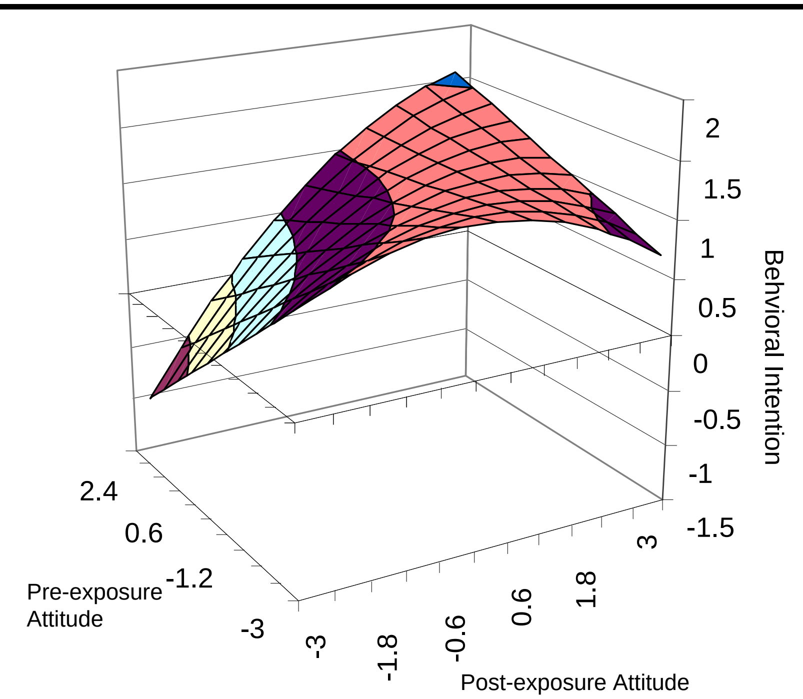

Figure 4. Response Surface for Attitude Predicting Behavioral Intention

H1a and H1b (test #1). Moreover, we found that there was no significant rotation of the surface along the disconfirmation axis because the slope of the second principal axis was not significantly different from -1 ($p < .01$; test #2). The linear slope of the response surface along the disconfirmation axis (quantity $b_1 - b_2$) was significant and positive, indicating that the influence of negative disconfirmation was stronger than the influence of positive disconfirmation, thus supporting H1c (test #3). The quadratic slope along the disconfirmation axis (quantity $b_3 - b_4 + b_5$) was significant, thus supporting H2a and H2b (test #5). We also found that the slope of the first principal axis was not significantly different from 1 ($p < .01$). This confirmed that the first principal axis ran parallel to the confirmation axis and supported H3 (test #5). Because the response surface was laterally shifted in the area where post-exposure attitude is slightly higher than pre-exposure attitude, behavioral intention to continue using a system was higher when users' post-exposure attitude was slightly higher than their pre-exposure attitude. The sign of the quadratic slope of the response surface along the disconfirmation axis (quantity $b_3 - b_4 + b_5$) was negative. The negative quadratic slope indicated that the surface along the disconfirmation axis was strongly concave, further supporting H1a and H1b.

In combination, these results indicated five key effects. First, behavioral intention decreased as post-exposure attitude deviated from the pre-exposure attitude in either direction. Therefore, positive or negative disconfirmation negatively influence behavioral intention. Second, the negative influence of disconfirmation becines stribger as the degree of disconfirmation increases. Third, as the surface had an overall positive slope along the confirmation axis, behavioral intention was higher when pre-exposure and post-exposure attitude were both high than when both were low. Fourth, the slight convex nature of the surface along the confirmation axis indicated that behavioral intention was lowest along the confirmation axis when both pre-exposure and post-exposure attitude were moderate (at the center) and increased in both directions. Fifth, the negative influence on behavioral intention was stronger in the case of negative disconfirmation when compared to the effect observed in the case of positive disconfirmation.

Post Hoc Analysis

As suggested earlier, consistent with the guidelines to test polynomial models (see Edwards 1994, 2002; Edwards and Rothbard 1999; Lambert et al. 2003), we used commensurate measurement (e.g., only usefulness—or attitude—and its associated higher-order terms were used to predict behavioral intention in a single model). Visual representation of response surfaces cannot be used to understand the relationships if more than one base construct (e.g., usefulness) and its related higher-order terms are used as predictors (Edwards 2002; Edwards and Parry 1993). However, to understand the joint effect of usefulness and attitude on behavioral intention and to see if the joint model helps us understand significantly higher variance over and above the individual models of usefulness and attitude, we conducted a *post hoc* analysis using usefulness, attitude, and their associated higher-order terms as predictors. The results of the analysis, shown in Table 5, indicated that the variance explained by the joint model (R^2 = 58%) was just marginally higher than the variance explained by the model using only usefulness and its higher-order terms as its predictor (R^2 = 56%). This is consistent with the technology acceptance literature that argues that attitude has a limited effect on behavioral intention when perceived usefulness and ease of use are present in the model (Venkatesh et al. 2003).

Discussion

The present research built upon and extended EDT research in IS (e.g., Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Ginzberg 1981; Staples et al. 2002; Szajna and Scamell 1993), and furthered our understanding of the phenomenon of post-adoption. First, we reviewed prior EDT research in IS. Second, we pointed to advances in methodologies and analytical techniques that would help us further our understanding of EDT research in IS. Third, drawing on cognitive dissonance theory and prospect theory, we proposed a polynomial model of expectation–disconfirmation in IS. Finally, we tested a baseline linear expectation–disconfirmation model and compared it to various versions of our polynomial model. The variance explained by the different models tested was (1) linear model, including both usefulness and attitude: 41 pecent; (2) polynomial model, including only usefulness: 56 percent; (3) polynomial model, including only attitude: 20 percent; and (4) polynomial model, including both usefulness and attitude: 58 percent.

Drawing from research on cognitive dissonance theory and prospect theory, we developed a polynomial model of expectation–disconfirmation in IS. This model argues that both positive and negative disconfirmation of usefulness (or attitude) expectations would have a negative influence on the user's behavioral intention to continue using a system. In the state of confirmation, there would be no adverse effect, thus resulting in higher levels of behavioral intention. However, one of the important tenets of our model is that when there is disconfirmation, even if it is in the positive direction, there

Table 5. Unconstrained Model: Predicting Behavioral Intention Using Usefulness and Attitude

		First-Order Linear Equation		Second-Order Quadratic Equation	
Dependent Variable	**Independent Variables**	**R^2**	**β**	**R^2**	**β**
Behavioral intention	U_1	.46	.18***	.58	.10**
	U_2		.58***		.30**
	A_1		-.08***		-.01
	A_2		.29***		.14***
	U_1^2				-.09***
	U_1U_2				.48***
	U_2^2				-.25***
	A_1^2				.04
	A_1A_2				.06**
	A_2^2				-.10**

Notes: U_1: Pre-exposure usefulness; U_2: Post-exposure usefulness; A_1: Pre-exposure attitude; A_2: Post-exposure attitude.
*p < .05; **p < .01; ***p < .001.

would be an adverse effect on the ultimate outcome (here, behavioral intention). Further, while positive disconfirmation has an adverse effect on intention, the effect of negative disconfirmation is stronger. We made the case that the complexity of the relationships and arguments made in our model could not be adequately captured by linear models, thus calling for the use of curvilinear models. Together, the proposed polynomial model, the discussion of the methodological and analytical advances to test the model, and the findings from the longitudinal empirical study represent important contributions to advancing the knowledge of EDT in IS.

One of our findings that warrants attention is the impact of pre- and post-exposure usefulness on behavioral intention. In contrast to our prediction, we found that the negative influence of positive disconfirmation on behavioral intention is as bad as negative disconfirmation. We draw from the realistic job preview (RJP) literature to explain this counterintuitive finding. A number of studies in the RJP literature have shown that organizational attractiveness can be increased if the job applicants develop realistic expectations about the new job (e.g., Hom et al. 1998, 1999; Irving and Meyer 1994; Thorsteinson et al. 2004). If the job applicants do not develop realistic expectations, but rather they develop unrealistically positive expectations about the job and have negative experiences, it casts doubt on the credibility and trustworthiness of the organization (Breaugh and Starke 2000; Wanous 1992). Drawing on this logic, it may be argued here that when the employees experience negative disconfirmation (high expectations and low experiences), they may have reduced intention to use the system because of the lack of credibility and trustworthiness of the system. When the job applicants develop unrealistically negative expectations, it may decrease their attraction to the organization (Bretz and Judge 1998). Using this line of reasoning in the context of this study, we surmise that users may have positive experiences, but they still might focus on the negative aspects (i.e., focus on what the system does not do for them rather than what the system does do for them). This, of course, is our *post hoc* interpretation and will benefit from future investigation that focuses more closely on comparing competing theoretical explanations.

Prior EDT research in IS suggested that confirmation of the initial beliefs would increase the satisfaction of users and, hence, increase behavioral intention to continue using a system (Bhattacherjee 2001; Ginzberg 1981). While we found support for this, our results provide additional insights. The level of behavioral intention depends on the absolute level of the confirmation. First, confirmation at low values of usefulness (or attitude) would result in a lower behavioral intention compared to confirmation at higher levels of usefulness (or attitude). This finding makes it important to know the absolute levels of usefulness/attitude because knowing only that a user's pre-exposure expectations were confirmed would not indicate whether the confirmation was achieved at high or low levels of usefulness/attitude. Second, the relationship between pre-exposure and post-exposure usefulness/attitude and behavioral intention is curvilinear in general and along the confirmation axis in particular, indicating that behavioral intention is lowest along the confirmation axis when confirmation is achieved at moderate values of usefulness and attitude.

Bhattacherjee and Premkumar (2004) provided preliminary evidence for a complex relationship between disconfirmation and the outcome variable by asserting that the empirical inconsistencies in classical EDT research can be resolved by separating positively and negatively disconfirmed groups. However, they did not examine the direct effect of positive and negative disconfirmation on behavioral intention. The results of our study show that positive disconfirmation is as bad as negative disconfirmation when it comes to the impact on behavioral intention. Therefore, setting high but realistic expectations about a system's usefulness and meeting those expectations is essential to foster the highest levels of behavioral intention, and unrealistic expectations would always result in fairly low levels of behavioral intention.

TAM contends that users' perceptions of usefulness will positively influence behavioral intention. However, we found that higher post-exposure usefulness resulted in lower behavioral intention when pre-exposure usefulness was quite low. This finding runs counter to the findings in classical marketing research that contends that consumers are more satisfied in the case of positive disconfirmation that happens when experience exceeds expectation (Churchill and Surprenant1982; Oliver et al. 1994). Therefore, classical EDT research recommended understatement of expectations so as to set low expectations, thus creating an opportunity to easily exceed them and, thus, maximize satisfaction**.** Szajna and Scamell (1993) noted that most of the studies related to expectations have been concerned with direction rather than degree of disconfirmation. Therefore, including the degree of disconfirmation, as we did here, was important to determine the effect of unrealistically high expectations on behavioral intention. Using polynomial modeling coupled with response surface methodology, we incorporated both the degree of disconfirmation and the direction of disconfirmation in our analysis and our findings confirmed that expectations should be set at a realistic level. While Bhattacherjee and Premkumar recommended that practitioners maintain realistic expectations, the use of direct measurement of disconfirmation prevented them from explicitly testing this recommendation in their study. Our study provides empirical evidence supporting this valuable insight in their work—suggesting that setting realistic expectations would foster the highest levels of behavioral intention to continue using a system.

There are two key limitations associated with the use of polynomial modeling that should be pointed out. First, polynomial modeling adopts the assumption of the standard regression analysis that component measures have minimal error and little or no bias. The coefficient estimates tend to be biased as the reliability of the component measures decreases. Moreover, this effect is more pronounced in the case of higher-order terms. Second, this methodology can be applied only to studies using congruence between component measures (e.g., pre-exposure and post-exposure usefulness).

Theoretical Implications and Future Research Directions

This study is one of the first studies in IS to use polynomial modeling and response surface methodology. Using the polynomial modeling approach, this study provided a richer and more accurate empirical evaluation of EDT in an IS context. Most of the research in IS has focused on linear models and used direct measures of disconfirmation (e.g., Susarla et al. 2003). As noted earlier, linear models fail to reveal complexities that are anticipated in theories of congruence (Edwards 1994, 2002; Edwards and Harrison 1993) and direct measurement distorts the joint effects of components on various outcomes (Irving and Meyer 1994, 1995, 1999). Further, disaggregating the component measures and examining the effect of individual measures on the outcome variable provides us information to develop more targeted interventions. Thus, it is important to reexamine other streams in IS research that employ the principle of congruence, such as IS service quality (see Kettinger and Lee 2005), where expectations and experiences could interact to influence outcomes.

There is a vast body of research studying met expectations in psychology, organizational behavior, and IS (e.g., Brown et al. 2008; Hecht and Allen 2005; Irving and Meyer 1994). Future research should focus on examining various competing models of expectation–disconfirmation in an IS context using the methodological and analytical approaches used here—namely, polynomial modeling and response surface methodology. These competing models of expectation–disconfirmation include assimilation (Holloway 1967; Oshikawa 1968), contrast (Hovland et al. 1957; Sherif and Hovland 1961), generalized negativity (Carlsmith and Aronson 1963), assimilation–contrast (Anderson 1973), expectations only, and experiences only. Such a study would help in determining the model that is most appropriate for the study of expectations and experiences in an IS context and will be a useful benchmark for our findings. Moreover, it would be beneficial for expectation–disconfirmation research to compare the results of direct measures with those of polynomial modeling in a single study.

Future research should also focus on testing more complex models of technology adoption, such as the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al. 2003), using the polynomial modeling approach. Most of these models have focused essentially on the linear relationships. Identifying possible curvilinear relationships in models, such as UTAUT, may present us with useful insights and enhance our understanding of the phenomenon of technology adoption and use. Further, advances in the area of moderation and mediation (e.g., Edwards and Lambert 2004) have allowed researchers to incorporate the effects of moderators and mediators into polynomial models in organizational behavior. Such analytical advances will help further research on complex models that can be compared to the model and pattern of findings that emerged in this paper. Also, such analysis would open up the possibility that a single model, such as UTAUT, with multiple constructs and their associated higher-order terms could explain more variance in behavioral intention than any of the models and, perhaps more importantly, lead us to even more accurate conclusions than prior EDT research in IS, UTAUT, or this study. In order to fully understand and compare these various models on an equal footing, a single study should be conducted that can test TAM, EDT, UTAUT, and the polynomial model proposed here.

Practical Implications

This study helps practitioners in solving the initial acceptance and subsequent discontinuance anomaly. The findings here call for managers to set realistic expectations about a system in order to develop a more favorable chance of users continuing to use the system in the long run. They should always attempt to set and achieve *high* expectations because behavioral intention to continue using a system is higher when pre-exposure expectations of usefulness are high and met, compared to when expectations of usefulness are low and met. The findings here also allude to building systems with a simple but clear purpose as, because behavioral intention is quite high even if fairly low expectations are set and met, that may well be the case with a system, that may not possess extensive functionality but rather a focused set of features.

There is risk involved in overselling information systems. Managers often try to oversell their system during the training sessions, thus resulting in users developing unrealistically high expectations. We recommend that managers focus on the basic and essential features of the system so as to set realistic expectations and meet them. One popular adage is to "underpromise and overdeliver." We strongly caution trainers and managers against following this popular adage so as to avoid the negative effects of positive disconfirmation.

We suggest that the managers should measure usefulness expectations and experiences separately in longitudinal settings and avoid the use of direct measurement. Such an approach would result in more accurate conclusions and provide useful diagnostic information in the setting being evaluated. Further, managers should maintain the distinction between expectations and experiences during the analysis. This approach would help managers directly see the separate interactive effects of usefulness expectations and experiences on behavioral intention. Moreover, disaggregating the disconfirmation measures would allow managers to specifically design interventions (e.g., training to increase users' usefulness expectations or system demonstration to increase users' usefulness experiences) that aim to optimize disconfirmation, recognizing that, in some cases, it may even be necessary to lower perceptions of post-exposure usefulness.

Conclusions

This research was aimed at furthering our understanding of post-adoption technology use. Prior EDT research used direct measurement for measuring disconfirmation and focused only on linear models. This resulted in a distortion of joint effects of pre-exposure and post-exposure usefulness and attitude on behavioral intention, and an oversimplification of the complex curvilinear relationships between the component measures. In this research, we drew from cognitive dissonance theory, realistic job preview, and prospect theory to develop a polynomial model of expectation–disconfirmation. The polynomial modeling coupled with the response surface modeling used in the current study provided a richer and more accurate understanding of expectation–disconfirmation as it related to technology adoption. Our study found support for the complex curvilinear models and indicated that the absolute level of confirmation determined behavioral intention for sustained use. Moreover, the curvilinear relationships between pre-exposure and post-exposure usefulness (or attitude) along the confirmation axis indicated that confirmation achieved at moderate values would result in lower behavioral intention as compared to confirmation achieved at high or low values of usefulness (or attitude). Based on these findings, we recommend managers set realistic and achievable expectations. Beyond the context-specific findings and implications, this work suggests the potential use for polynomial modeling and response surface methodology as meaningful analytical techniques to deepen our understanding of other important IS phenomena.

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Appendix

Questionnaire Items

Perceived Usefulness (t_1):
1. I would find the <system> useful in my job (Strongly disagree…Strongly agree).
2. Using the <system> in my job would enable me to accomplish tasks more quickly (Strongly disagree…Strongly agree).
3. Using the <system> would increase my productivity (Strongly disagree…Strongly agree).
4. Using the <system> would improve my job performance (Strongly disagree…Strongly agree).

Attitude toward using technology (t_1):
1. Using the <system> will be a bad/good idea (Strongly disagree…Strongly agree).
2. The <system> will make work more interesting (Strongly disagree…Strongly agree).
3. Working with the <system> will be fun (Strongly disagree…Strongly agree).
4. I would like working with the <system> (Strongly disagree…Strongly agree).

Perceived Usefulness (t_2):
1. I find the <system> useful in my job (Strongly disagree…Strongly agree).
2. Using the <system> enables me to accomplish tasks more quickly (Strongly disagree…Strongly agree).
3. Using the <system> increases my productivity (Strongly disagree…Strongly agree).
4. Using the <system> improves my job performance (Strongly disagree…Strongly agree).

Attitude toward using technology (t_2):
1. Using the <system> is a bad/good idea (Strongly disagree…Strongly agree).
2. The <system> makes work more interesting (Strongly disagree…Strongly agree).
3. Working with the <system> is fun (Strongly disagree…Strongly agree).
4. I like working with the <system> (Strongly disagree…Strongly agree).

Behavioral intention to use the <system> (t_2):
1. I intend to continue using the <system> (Strongly disagree…Strongly agree).
2. I predict I would continue using the <system> (Strongly disagree…Strongly agree).
3. I plan to continue using the <system> (Strongly disagree…Strongly agree).