

Expectation Confirmation in Technology Use

Susan A. Brown

Department of Management Information Systems, Eller College of Management, University of Arizona,
Tucson, Arizona 85721, suebrown@eller.arizona.edu

Viswanath Venkatesh

Walton College of Business, University of Arkansas, Fayetteville, Arkansas 72701, vvenkatesh@vvenkatesh.us

Sandeep Goyal

College of Business, University of Southern Indiana, Evansville, Indiana 47712, Sandeep@sandeepgoyal.com

We propose a model to study expectation confirmation in information systems. The proposed model is based on the assimilation-contrast model and prospect theory, and suggests that both are needed to account for the magnitude and direction of the deviations between experiences and expectations. Using the technology acceptance model's (TAM) primary construct—namely, perceived usefulness—expectations and experiences were conceptualized and operationalized to test our model. Data were collected in a field study from 1,113 participants at two points in time. Using polynomial modeling and response surface analysis, we demonstrated that our model offers a good explanation of the relationship among information systems expectations, experiences, and use. We discuss theoretical and practical implications.

Key words: technology acceptance; TAM; cognitive dissonance theory; polynomial modeling; response surface analysis

History: Ritu Agarwal, Senior Editor; Sung A. Kim, Associate Editor. This paper was received on March 4, 2007, and was with the authors 30 months for 3 revisions. Published online in *Articles in Advance*.

Introduction

The relationship between a priori user expectations, a posteriori evaluations (experiences), and key outcomes associated with information systems (IS) implementations has been a topic of interest for nearly three decades (e.g., Bhattacharjee 2001, Ginzberg 1981, Staples et al. 2002, Szajna and Scamell 1993). Research on expectation confirmation has also been conducted in other fields, and impressive progress has been made in our understanding of the phenomenon in general and within the IS context in particular. However, CIOs still consider unknown or unrealistic expectations on the part of the employees to be among the top five hurdles to success of IS implementations (Prewitt and Ware 2006), and given that the challenge of underutilized systems remains (Ong and Lai 2006), understanding the expectation-experience gap and its implications for technology use will be of great value to both research and practice.

Competing models of expectation confirmation, with different underlying theoretical explanations, have been put forth in IS, organizational behavior, marketing, and psychology (e.g., Anderson 1973; Klein 1999; Oliver 1977, 1980; Yi 1990). The models vary in terms of their prescriptions on how expectations should be set in order to produce desirable outcomes. There is also a long history of research on expectations and IS outcomes (e.g., Bhattacharjee 2001, Ginzberg 1981, Staples et al. 2002, Szajna

and Scamell 1993). Even though the underlying theories predict nonlinear effects, much of the empirical support in prior work testing the complex propositions of the models has used linear models/equations and associated analyses (e.g., Boulding et al. 1993, Caligiuri et al. 2001, Churchill and Suprenant 1982, McElroy et al. 1996, Szajna and Scamell 1993). In expectation confirmation research, the assumption of linearity implies similar effects at all levels of expectations and/or experiences. However, the assumption of linearity may oversimplify the relationships and mask the true relationships among the component measures (e.g., Edwards 2002, Edwards and Cooper 1990, Edwards and Rothbard 1999, Irving and Meyer 1994, Staples et al. 2002). Further, higher-order terms in the nonlinear models could explain significant variance not explained by linear models (Edwards 2001). Consequently, the magnitude and direction of differences between expectations and experiences could have differential impacts on the outcome(s). Thus, the use of linear modeling constrains our ability to discern the complex patterns theorized. In fact, in their posthoc analysis, Staples et al. (2002) provide some evidence that nonlinear relationships may exist between expectations, experiences, and outcomes. By staying true to the theoretical perspectives that suggest nonlinear relationships, polynomial modeling, coupled with response surface analysis to interpret

them, can provide valuable insights into the impact of expectations on important dependent variables in IS.

We employ the technology acceptance model (TAM; Davis et al. 1989) to study the impact of expectations and experiences on technology use. We further draw from an integrated assimilation-contrast model, which has its roots in cognitive dissonance theory (Festinger 1962) and disconfirmation theory (Churchill and Suprenant 1982, Patterson et al. 1997), and prospect theory (Kahneman and Tversky 1979, 1984; Tversky and Kahneman 1991) to develop our model. Against this backdrop, we have two related objectives in this study. First, we propose a model that integrates different theoretical perspectives in order to consider the magnitude *and* direction of disconfirmation at various points of expectations and experiences. As noted earlier, we use TAM to identify the constructs about which user expectations, experiences, and outcomes will be assessed. The vast body of research on TAM has typically examined intention and use as a linear function of both perceived usefulness and perceived ease of use. Further, in most cases, either expectations (preuse beliefs) or experiences (postuse beliefs) are used as predictors (e.g., Straub et al. 1995; for a review, see Venkatesh et al. 2003), but seldom have they been examined in a single model (cf. Brown et al. 2008, Szjana and Scamell 1993). Our second objective is to test the proposed model in a study conducted in an organizational setting that includes data about expectations, experiences, and use of a new technology. In order to fully test the model and relax the linearity assumptions of prior work, we draw on and extend prior work on polynomial modeling and response surface analysis in organizational behavior (see Edwards 1995, Edwards and Harrison 1993, Edwards and Parry 1993). Accomplishing these objectives will help us contribute a new way of thinking to the growing body of knowledge, both on expectation confirmation in general and expectation confirmation in IS in particular. Also, although technology acceptance research is mature, little research in this domain has theoretically or empirically examined how expectations and experiences about key beliefs can together influence technology use, and by addressing this gap, we seek to provide a richer and more dynamic view of technology use. Finally, we will extend prior work on polynomial modeling and response surface analysis that has primarily employed quadratic models by examining the higher-order effects and presenting the necessary statistical tests to empirically assess the support for our proposed model.

1. Theory

TAM has been the focus of several studies that examine individuals' beliefs, intention to use, and technology use. TAM employs perceived ease of use and

perceived usefulness as the determinants of intention, which in turn determines use. Perceived ease of use is defined as the degree to which an individual believes using a system is relatively free from effort, and perceived usefulness is defined as the degree to which an individual believes using the system enhances an individual's effectiveness (Davis et al. 1989). Given that TAM is widely used and specifies the relationship between beliefs and an important measure of system success—i.e., technology use (see DeLone and McLean 1992, 2003; Venkatesh et al. 2003)—TAM provides a contextual basis to test the models of expectation confirmation given that expectation confirmation research is always conducted in a particular context, such as consumer products, jobs, and IS. The preponderance of the evidence demonstrates that perceived usefulness is the strongest determinant of intention and use (see Venkatesh et al. 2003).¹ In fact, some research demonstrates that ease of use has a non-significant direct impact (Agarwal and Prasad 1998). Related research has shown that perceptions of ease of use frequently influence intention or use indirectly through usefulness such that the effect of ease of use is fully mediated by usefulness (e.g., Venkatesh et al. 2003). The importance of usefulness is further fortified by the strong correlations of intentions over time (Davis and Venkatesh 2004) and the impact of habit, driven by intention, on use over time (see Kim and Malhotra 2005, Limayem et al. 2007). Thus, in the current study, we focus on expectations and experiences associated with usefulness and control for the effect of ease of use.

1.1. Hypothesis Development

With respect to a user's perceptions of a system's usefulness, expectations are typically developed during the preimplementation kickoff and/or during training sessions. At this point, users evaluate the system in terms of how it will play a role in their jobs. Essentially, they are forming expectations associated with system qualities, such as its ability to help them perform tasks more quickly, improve their efficiency, and increase the quality of their work (Venkatesh and Davis 2000). During this preuse stage, users are cognitively forming the level of usefulness that will be acceptable to them, such that if the system performs at that level (or better), they will use it.

One consistent aspect of the different theories that have been used to study expectations, and what we

¹ We drop intention from the model and examine the effect of beliefs directly on use because intention is meant to serve as a proxy for behavior when behavior itself cannot be measured (Ajzen 1991). Further, examining use directly, especially if it can be measured objectively, minimizes potential common method biases (e.g., Straub et al. 1995).

believe is an important theoretical reason for conflicting findings in prior work, is that the theories used in prior work do not have different predictions when it comes to the *magnitude and direction* of deviation from an ideal point (i.e., when expectations are met). The assimilation-contrast model (see Anderson 1973) addresses this issue by treating small and large deviations differently, but there is still an assumption that the total magnitude of the impact will be the same regardless of whether the deviation is in the positive or negative direction. If differences are relatively small such that they fall within the *zone of tolerance* (Berry and Parasuraman 1991, Johnston 1995, Kennedy and Thirkell 1988), there will be little, if any, adjustment made and outcomes will be assimilated toward expectations, consistent with cognitive dissonance theory (Festinger 1962)—i.e., expectations create inertia in which outcomes are consistent with expectations as long as experiences are not outside of a set range (Liljander and Strandvik 1993). In contrast, when differences are outside such a zone of tolerance, outcome evaluations are based on the magnitude of the gap between expectations and experiences, and ultimately biased in the direction of experiences, consistent with disconfirmation theory (Churchill and Suprenant 1982, Patterson et al. 1997).

In IS research, Szajna and Scamell (1993) used cognitive dissonance theory to demonstrate the impact of expectations—specifically, setting low or high expectations relative to the actual system—and found that outcome evaluations assimilated toward expectations. In contrast, Bhattacharjee (2001) used and found support for disconfirmation theory (Churchill and Suprenant 1982, Patterson et al. 1997). It is possible that these differences can be explained by examining the magnitude of the deviations. For example, in the controlled experimental environment of Szajna and Scamell's (1993) study, it is possible that the magnitude of deviation was small enough that it fell within the zone of tolerance, and thus supported an assimilation view (i.e., cognitive dissonance theory). In contrast, in the real-world setting of Bhattacharjee's (2001) study, the deviations may have been outside that zone, thus supporting a contrast view (i.e., disconfirmation theory).

In an IS implementation context, users typically recognize that the system will not meet all of their expectations (Prewitt and Ware 2006). Small deviations will fall within the zone of tolerance, and in essence, users will view their experiences as assimilating in large part to their expectations. In such cases, small deviations are likely to be received without much of a positive or negative consequence. The consequent use of the technology will thus be driven by the initial expectations when the deviation is small—e.g., if the expectations of usefulness were high, the use of the

technology will be high even if the actual system is slightly more or less useful. Thus, we hypothesize:

HYPOTHESIS 1. *As the magnitude of expectation disconfirmation decreases, expectations will have a direct, positive effect on use.*

Our second hypothesis relates to what happens when the deviation between expectations and experiences increases. Intuitively, it does not stand to reason that an individual who gets more from a system than she expected would want to use it less. If we adhere to the notion that expectations establish the acceptable level, then it makes sense that meeting that level is good, and exceeding it, especially substantially, is better. When a user is given a system that offers much more by way of opportunities to enhance productivity, i.e., high experienced usefulness, she or he might explore the various features in hopes of enhancing productivity above and beyond what the initial expectations were. Furthermore, the fact that the initial expectations were significantly exceeded will increase the credibility of the system, prompting the user to explore the features that he or she did not expect to have. Such feature exploration is considered an important aspect of use (Jasperson et al. 2005).

When actual experiences fall below expectations—i.e., negative disconfirmation—especially when the extent of disconfirmation is high, we would expect low levels of the outcome variable. For instance, in consumer behavior studies, there is evidence demonstrating that consumers are highly dissatisfied when the product experiences fall well short of expectations (Bearden and Teel 1983; see Szymanski and Henard 2000 for a meta-analysis; see Yi 1990 for a review). In the context of technology use, when the perceptions of usefulness are far below expected levels, users essentially do not find many of the features that they believe will enhance their productivity. Not only does this create a situation where a user cannot meaningfully use the technology, but also the resulting disappointment could lead to the user not using even those features that the system does provide (McAfee 2003). Thus, the resulting level of use in situations of high disconfirmation will be very low to nonexistent. Although the different theoretical perspectives used in prior empirical work predict slightly different magnitudes of impact, they are consistent in predicting a negative outcome. We specifically expect very low levels of use to be the outcome of high negative disconfirmation.

A question remains, however, regarding the relative impact of positive and negative disconfirmation. To address that question, we turn to prospect theory (Kahneman and Tversky 1979). Although a model of decision making under uncertainty, prospect theory has been leveraged to understand other issues,

such as the development of customer satisfaction (e.g., Anderson and Sullivan 1993). Kahneman and Tversky (1979) introduced prospect theory, in part, to explain why people's decisions violated the expectations set forth in expected utility theory. In examining decisions, empirical evidence clearly demonstrated that individuals did not always select the choice that would result in the largest benefit. They argued that the rational expected utility model did not account for the idea that losses were weighted more heavily than gains (Kahneman and Tversky 1984, Tversky and Kahneman 1991). Prospect theory proposes that the value function is "concave for gains, convex for losses, and steeper for losses than for gains" (Tversky and Kahneman 1992, p. 297). In essence, prospect theory suggests that negative disconfirmation will have a greater negative impact on outcome evaluations than positive disconfirmation will have in the positive direction because losses loom larger than gains.

The theories used in prior empirical work assume that the effects of positive and negative disconfirmations are relatively equal. Prospect theory, however, proposes that losses—i.e., in our case, negative deviations—will have a greater impact on decision making than will gains. Thus, from an expectation-experience gap perspective, negative disconfirmation will have a greater negative impact on use than positive disconfirmation will have in the positive direction. For an expected level of usefulness, the basic tenet of prospect theory suggests that the negative effect of a given level of negative disconfirmation on use would be greater in absolute terms than the positive effect of the corresponding level of positive disconfirmation. As noted earlier, positive disconfirmation may prompt the user to engage in exploratory behaviors related to the unexpected positive features and functionalities. However, the negative disconfirmation situation can spawn avoidance behaviors. The fact that a system fails to provide necessary and expected functionalities to enhance productivity could prompt a user to engage in workarounds, shortcuts, or other dysfunctional behaviors to completely avoid using the system (see Boudreau and Robey 2005, McAfee 2003). Together, this suggests a disproportionately higher negative effect of negative disconfirmation when compared to the positive effect of positive disconfirmation. Thus, we hypothesize as follows.

HYPOTHESIS 2. *As the magnitude of expectation disconfirmation increases, the increase in use associated with positive disconfirmation will be significantly smaller than the decrease in use associated with the same level of negative disconfirmation.*

2. Method

In this section, we discuss the organizational setting, participants, and procedure, followed by details of our measures.

2.1. Organizational Setting, Participants, and Data Collection Procedure

The setting for the study was an Intranet-based system for knowledge sharing within a large organization with nearly 8,000 employees, in the telecommunications industry. In addition to providing all information to employees from the human resource department, the system could be used by employees to share information, related to both work and social activities, e.g., including benefits, forms, and personal interest groups. The organization's objective with the system was to create a better information flow from the organization to its employees, provide a basic knowledge management system to facilitate sharing of work-related information among employees, and provide a bulletin board service to allow employees to share personal/social interests and increase social interactions among employees across various parts of the organization. Even after the system was introduced, the previously available options (e.g., paper-based, other systems) continued to be available for the entire duration of our study, thus rendering the use of the system to be voluntary.

The sampling frame was a list of the nearly 8,000 employees in the organization. We contacted the heads of various business units to seek permission to contact the employees. Most business unit heads suggested choosing somewhere between 25% and 50% of the employees at random. This led to a revised sampling frame of 2,400 employees. We contacted these employees by e-mail to solicit their participation. We received responses from 1,601 employees in the first wave of data collection and 1,113 of those employees provided usable responses in the second wave of measurement also and allowed us access to their usage logs, resulting in an overall response rate just over 46%. Of the 1,113 responses, about a third were women and the average age was just about 35 (SD ~ 10). The demographic profile of the respondents matched the profile of the sampling frame. The demographic profiles of the respondents from the first and second waves of data were comparable. Also, the nonrespondents from the first to the second wave had a similar demographic profile to the respondents in the first wave. Taken together, this pattern of results alleviates concerns about nonresponse bias.

We administered two surveys, both in year 2005. The first survey was administered immediately after the completion of the organizationally required training program on the new system (t_1), and respondents

returned it within a week of administration. The second survey was administered after the users had a substantial amount of time to use the technology—i.e., six months (t_2). We measured expectations at t_1 and experiences at t_2 . Again, respondents returned the survey within a week. Prior research operationalized expectations by determining specific expectations regarding the new system along with key determinants of implementation success, such as attitude and beliefs towards the system (e.g., Bhattacharjee and Premkumar 2004). We operationalized expectations by measuring users' perceptions of usefulness and ease of use towards using the system being implemented. Data about technology use were obtained from system logs for a year starting from t_1 , although we employed use data collected after t_2 as the dependent variable and the early-use data were used as a control variable. This approach is consistent with prior expectation confirmation, training, and technology acceptance research where individual reactions to the technology were studied (e.g., Bhattacharjee and Premkumar 2004, Davis et al. 1989, Venkatesh et al. 2003).

2.2. Measurement

A questionnaire was created with items validated in prior research. Perceived usefulness and perceived ease of use were measured using four-item scales adapted from prior research (see Bhattacharjee and Premkumar 2004, Venkatesh et al. 2003). Various modified versions of these scales have been used extensively in prior research (e.g., Agarwal and Prasad 1998, Venkatesh and Davis 2000). Seven-point Likert agreement scales were used in conjunction with the items, with 1 being "strongly disagree" and 7 being "strongly agree." The items were worded appropriately to measure expectations immediately after training and experiences six months after implementation. Consistent with some prior research, actual use was operationalized using system log data of the duration of use (in hours) less idle time (e.g., Venkatesh et al. 2003). This measure provides the advantage of eliminating common method bias and limits the potential for social desirability biases given the elimination of idle time.

3. Data Analysis Approach

In this section, we discuss the basics of polynomial modeling, response surface methodology, and the analytical representation of the models to be tested.

3.1. Polynomial Modeling

Polynomial modeling uses hierarchical analysis of polynomial equations and may be applied in a confirmatory or an exploratory manner (Edwards 2001). The confirmatory approach involves identification of

the regression equation corresponding to the theoretical model and relaxing the constraints the model specifies. These constraints are used as hypotheses for falsification. The theoretical model is supported if: (1) variance explained by the relaxed equation differs significantly from zero; (2) all constraints imposed by the theoretical model are satisfied; (3) all coefficients of the regression equation follow the appropriate pattern; and (4) the variance explained by the higher-order terms (i.e., higher than those in the equation) does not substantively differ from zero. For example, a squared difference score equation can be shown:

$$\begin{aligned} Z &= b_0 + b_1(X - Y)^2 + e \quad (\text{or}) \\ Z &= b_0 + b_1X^2 - 2b_1XY + b_1Y^2 + e. \end{aligned} \quad (1)$$

The relaxed form of Equation (1) can be

$$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e. \quad (2)$$

Support for the theoretical model rests on the conditions that: (1) Equation (2) explains significant variance in the outcome variable Z ; (2) constraints on Equation (2) (e.g., $b_3 = b_5$ and $b_3 + b_4 + b_5 = 0$) are satisfied; (3) the coefficients follow the appropriate pattern (e.g., $b_1 = 0$, $b_2 = 0$); and (4) variance explained by the set of terms one order higher than those in Equation (2) does not significantly differ from zero.

3.2. Response Surface Methodology

Polynomial models often yield higher-order polynomial equations that are difficult to interpret (Edwards 2001). Response surface methodology is a visual aid to get a richer and a deeper understanding of such polynomial equations. Edwards and Parry (1993) define the response surface methodology as an interpretive framework to show how the coefficients of the polynomial equation test the surfaces they imply. This methodology concentrates on three key features of response surfaces: (1) *stationary point*, which is defined as a point at which slope of the surface is zero in all directions; (2) *principal axes*, which are defined as lines running perpendicular to each other and intersecting at the stationary point (the slope of a convex surface is maximum along the first principal axis and minimum along the second principal axis and the slope of the concave surface is minimum along the first principal axis and maximum along the second principal axis); and (3) *slopes along lines of interest*, such as the confirmation axis, the disconfirmation axis, and principal axes, with the confirmation axis being the line where there is congruence between the component measures (i.e., both the components are equal) and the disconfirmation axis being the line that runs perpendicular to the confirmation axis.

Much prior research (e.g., Edwards and Harrison 1993, Edwards and Parry 1993) has primarily focused

only up to the second-order polynomial equations because key response surface features, such as the stationary point and principal axes, are not available for third-order polynomial equations. However, the slope of the surface along the confirmation and the disconfirmation axes can be used, as in the second-order model. Thus, for our analysis of the third-order cubic equation, we rely on the slope along confirmation and disconfirmation axes. The general third-order polynomial equation is given by

$$Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + b_6U_1^3 + b_7U_1^2U_2 + b_8U_1U_2^2 + b_9U_2^3 + e. \quad (3)$$

Where, $Z = \text{Use}$; $U_1 = \text{Experienced usefulness}$; $U_2 = \text{Expected usefulness}$

Along the confirmation axis: Experienced usefulness = Expected usefulness—i.e., $U_1 = U_2$.

Therefore, Equation (3) can be written as

$$Z = b_0 + (b_1 + b_2)U + (b_3 + b_4 + b_5)U^2 + (b_6 + b_7 + b_8 + b_9)U^3 + e. \quad (4)$$

Along the disconfirmation axis: Experienced usefulness = –Expected usefulness—i.e., $U_1 = -U_2$

Therefore, Equation (3) can be written as

$$Z = b_0 + (b_1 - b_2)U + (b_3 - b_4 + b_5)U^2 + (b_6 - b_7 + b_8 - b_9)U^3 + e. \quad (5)$$

Equations (4) and (5) show that the cubic slopes of the surface along the confirmation axis (a_x^3) and disconfirmation axis (a_y^3) are given by the quantities $(b_6 + b_7 + b_8 + b_9)$ and $(b_6 - b_7 + b_8 - b_9)$, respectively.

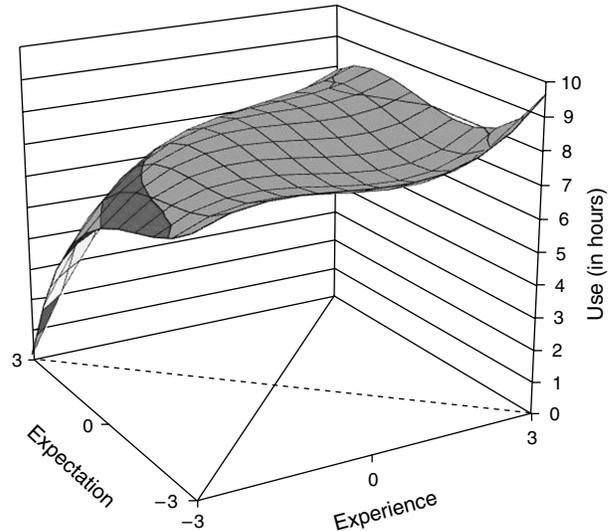
3.3. Proposed Model

Our proposed model integrates the assimilation-contrast model and prospect theory. Our model argues that when the magnitude of expectation disconfirmation is small, technology use is driven by initial expectations such that expectations will have a direct positive effect on use. However, when the magnitude of expectation disconfirmation is large, technology use is driven by the size and direction of the disconfirmation such that positive disconfirmation would result in high levels of use and negative disconfirmation would result in low levels of use, with negative impacts larger than positive impacts. A three-dimensional depiction of the proposed model is shown in Figure 1 and can be represented by the following equation:

$$Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + b_6U_1^3 + b_7U_1^2U_2 + b_8U_1U_2^2 + b_9U_2^3 + e, \quad (6)$$

where $Z = \text{Use}$; $U_1 = \text{Experienced usefulness}$; $U_2 = \text{Expected usefulness}$.

Figure 1 Three-Dimensional Plots of the Theoretical Model



Note. The solid line running diagonally from the near corner to the far corner represents the confirmation axis (experiences = expectations), and the dotted line diagonally left to right represents the disconfirmation line (experiences = –expectations).

H1 suggests that as the magnitude of expectation disconfirmation decreases, the effect on use will be consistent with expectations. In other words, even when users experience negative disconfirmation (experiences are less than expectations), for low magnitudes of expectation disconfirmation, the effect on use will follow expectations such that the slope of the surface is expected to be positive—i.e., the higher the expectations, the higher the use. In contrast, H2 suggests that when users experience negative disconfirmation, for high magnitudes of expectation disconfirmation, the effect on use will *not* follow expectations such that slope of the surface is expected to be negative—i.e., the higher the expectations, the lower the use. Taken together, for negative disconfirmation, H1 and H2 suggest that as we move away from the ideal point (expectation = experience), the slope of the surface first increases (as deviations are low) and then increases (as deviations are high), indicating an inflection point. Following the same line of reasoning, for positive disconfirmation, H1 and H2 together suggest that as we move away from the ideal point, the slope of the surface first decreases (as deviations are low) and then increases (as deviations are high), indicating another inflection point. A test for such a surface with two inflection points along a line (i.e., disconfirmation axis) would require the cubic slope of the surface along the disconfirmation axis to be significant and positive.

Prior technology acceptance literature suggests that high levels of both expectations and experiences of usefulness would result in a higher outcome (e.g., use) than low levels of expectations and experiences

(see Venkatesh et al. 2003). Therefore, we expect the confirmation axis to have a positive and linear slope. Finally, H2 also suggests that the increase in use associated with positive disconfirmation is smaller than the decrease in use associated with negative disconfirmation. The support for this hypothesis would require the slope of the surface along the disconfirmation axis for negative disconfirmation to be greater than the slope of the surface along the disconfirmation axis for positive disconfirmation. These tests can be summarized as:

- Test 1. $a_y^3 > 0$;
- Test 2. $a_x > 0$;
- Test 3. $a_x^2 = 0$;
- Test 4. $a_x^3 = 0$; and
- Test 5. $a_{y(\text{negative disconfirmation})} > a_{y(\text{positive disconfirmation})}$.

4. Results

4.1. Preliminary Analysis

We screened the data set for outliers using Cook's D and standardized residuals from regression equations. We excluded six cases based on the criteria set forth in Bollen and Jackman (1990). In conducting the analysis, measures of expectations and experiences were calculated by averaging the scale-centered item measures for perceived usefulness. Scale centering is done by subtracting the scale midpoints from the actual score. Scale centering reduces multicollinearity problems and allows meaningful interpretation of the coefficients of the polynomial equations (Edwards 2002). Scores produced after scale centering ranged from -3 to $+3$. The VIFs for all the variables, including interaction and higher-order terms, were below 4, indicating that the data did not suffer from any potential multicollinearity problems. Further, we conducted Harmon's one-factor test and partial correlation procedure to check for the problems associated with common method bias (Podsakoff and Organ 1986). In the Harmon's one-factor test, all the variables of interest were entered into a factor analysis to check whether: (1) a single factor emerges from the factor analysis; and (2) one single factor accounts for majority of the covariance in the interdependent and criterion variable. We found that neither of the two conditions was true. In the partial correlation procedure, the first factor from the unrotated factor pattern was entered into the linear regression model as a control variable to check whether a meaningful relationship among the variables of the interest exists even after first factor was controlled (for a review, see Podsakoff and Organ 1986). Because this condition was also satisfied, we concluded that common method bias was not a problem in our data set. Given that we used similar items to measure expectations and experiences, it is likely to produce correlated measurement errors between items. However,

the residual plots showed that there were no specific patterns. Furthermore, we found that the Durbin-Watson test statistic is not significant at the 0.05 level, confirming that the data did not suffer from a correlated measurement error problem.

Bootstrapping and jackknifing are both options to determine the significance level of the various components of the response surfaces, such as the slopes of confirmation and disconfirmation axes, but given our large sample size, as suggested by Edwards and Parry (1993), we used a jackknife procedure. For all analyses, U_1 represents experienced usefulness, U_2 represents expected usefulness, and Z represents use. All measurement scales showed high reliability, with the Cronbach alpha coefficients exceeding 0.80 in all cases. The mean of all the scales was above the midpoint of 4 (0 after scale centering), and the standard deviation was above 1. Because higher-order terms are mathematically calculated from lower-order terms, it comes as no surprise that they are highly correlated with lower-order terms and other higher-order terms. Also, experienced usefulness had the highest correlation with the dependent variable of use. Table 1 shows the descriptive statistics and correlations for all variables. Construct validity was strongly supported by principal components analysis with varimax rotation that yielded a five-factor solution, as expected. These results supported internal consistency, with all loadings greater than 0.80, and discriminant validity with all cross loadings less than 0.30; the specific results are not shown here given the consistency with much prior technology adoption (e.g., Davis 1989, Venkatesh and Davis 2000).

4.2. Hypotheses Testing

We used polynomial regression analysis to test our hypotheses. We began with the examination of unconstrained regression equations, shown in Table 2. Because the F -test ($p < 0.01$) showed that the variance explained by the cubic equation ($R^2 = 0.70$) was significantly higher than both the linear equation ($R^2 = 0.35$) and the quadratic equation ($R^2 = 0.51$), we used the cubic equation to test our hypotheses. We also examined the fourth-order equation to see if it explained significantly higher variance than the cubic equation. The results of the F -test showed that this is not the case, confirming that the cubic equation is appropriate to test our hypotheses.

We tested our hypotheses using a two-dimensional plot predicting technology use for three different levels (low, medium, high) of expectations and experiences (see Figure 2) and a three-dimensional response surface (see Figure 3). Consistent results in both cases provided support for our hypotheses. H1 suggested that as the magnitude of expectation disconfirmation decreases, the effect on use will be consistent

Table 1 Descriptive Statistics and Correlations

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Gender	0.34	0.46														
2 Age	35.92	9.97	0.20***													
3 EOU ₁	3.90	1.22	0.20***	-0.23***												
4 EOU ₂	4.30	1.30	0.23***	-0.26***	0.05											
5 Use ₁₂	4.22	1.16	0.15*	-0.15*	0.14*	0.17**										
6 U ₁	3.84	1.17	0.16**	-0.19**	0.25***	0.18**	0.44***									
7 U ₂	4.43	1.11	0.23***	-0.21***	0.15*	0.19**	0.29***	0.03***								
8 U ₁ ²	5.47	1.06	0.19**	-0.20***	0.23***	0.21***	-0.30***	0.17**	-0.02							
9 U ₁ U ₂	3.96	1.37	0.24***	-0.21***	0.07	0.17*	0.28***	0.26***	-0.05	-0.01						
10 U ₂ ²	5.39	1.07	0.17**	-0.27***	0.17**	0.19**	-0.17**	0.04	0.38***	-0.05	-0.01					
11 U ₁ ³	3.29	7.16	0.28***	-0.31***	0.21***	0.24***	0.46***	0.71***	0.02	-0.35***	0.18**	0.06				
12 U ₁ ² U ₂	4.46	2.80	0.19**	-0.28***	0.20***	0.23***	-0.10	-0.01	0.52***	0.21***	-0.09	0.20***	0.08			
13 U ₁ U ₂ ²	3.85	2.66	0.25***	-0.27***	0.23***	0.26***	0.28***	0.55***	-0.02	-0.01	0.47***	0.03	0.36***	-0.003		
14 U ₂ ³	5.36	4.11	0.20***	-0.24***	0.21***	0.24***	-0.17**	0.01	0.70***	-0.01	-0.01	0.56***	0.01	0.38***	-0.01	
15 Use ₂₃	7.43	6.01	0.17**	-0.19**	0.17**	0.22***	0.33***	0.37***	0.27***	-0.43***	0.40***	-0.22***	0.57***	-0.13*	0.39***	-0.19**

Notes. Use₂₃: Use measured after t_2 ; Use₁₂: Use measured between t_1 and t_2 ; EOU₁: Experienced ease of use; EOU₂: Expected ease of use; U₁ = Experienced usefulness; U₂ = Expected usefulness. Control variables: EOU₁, EOU₂, Gender (1 represents women), and Age. Variables measured at time t_1 : EOU₁, U₁, Gender, and Age. Variable measured at time t_2 : EOU₂, U₂, and Use.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

with expectations. We tested this hypothesis by examining the level of use when users had a moderate ($U_1 = 0$ on a scale-centered seven-point scale) experience using the system. In order to do so, we used a value of 0 (moderate experience) for U_1 in the unconstrained cubic regression model presented in Table 2 to develop an equation for usefulness expectations predicting use. We also developed equations for the high ($U_1 = 3$) and the low experience ($U_1 = -3$) to test H2. These equations were then used to plot Figure 2, which shows the level of use for different values of expectations—i.e., -3 (low expectation), 0 (moderate expectation), and 3 (high expectation). Oliver (1977)

argues that negative disconfirmation is represented by the scenario where experiences are less than expectations (e.g., $U_1 = -3$ and $U_2 = 3$) and positive disconfirmation is represented by the scenario where expectations are less than experiences (e.g., $U_1 = 3$ and $U_2 = -3$). For small magnitude of disconfirmation, we found that the level of use increased with higher levels of expectations. The linear slope for moderate disconfirmation was found to be positive and significant (slope = 0.18, $p < 0.01$), indicating that for moderate experience levels, the level of use increased with the increase in usefulness expectation, providing support for H1. For extreme levels of experiences—i.e.,

Table 2 Unconstrained Model: Predicting Use Using Usefulness

Dependent variable	Independent variable	First-order linear equation			Second-order quadratic equation			Third-order cubic equation		
		R ²	B	SE	R ²	B	SE	R ²	B	SE
Use ₂₃	Age	0.35	-0.10	0.01	0.51	-0.12	0.02	0.70	-0.11	0.02
	Gender		0.19*	0.02		0.23*	0.02		0.10	0.02
	EOU ₁		0.05	0.04		0.06	0.02		0.05	0.02
	EOU ₂		0.20*	0.02		0.15	0.02		0.09	0.02
	Use ₁₂		0.48***	0.04		0.25**	0.04		0.14*	0.03
	U ₁		1.16***	0.06		0.72***	0.03		-1.19***	0.02
	U ₂		0.64**	0.05		1.23***	0.04		2.87***	0.07
	U ₁ ²					-0.70***	0.02		-0.31***	0.02
	U ₁ U ₂					0.98***	0.03		0.74***	0.03
	U ₂ ²					-0.74***	0.02		-0.33***	0.02
	U ₁ ³								0.34***	0.01
	U ₁ ² U ₂								-0.43***	0.01
	U ₁ U ₂ ²								0.32***	0.01
	U ₂ ³								-0.40***	0.02

Notes. Use₂₃: Use measured after t_2 ; Use₁₂: Use measured between t_1 and t_2 ; EOU₁: Experienced ease of use; EOU₂: Expected ease of use; U₁ = Experienced usefulness; U₂ = Expected usefulness. Control variables: EOU₁, EOU₂, Gender (1 represents women), and Age. Variables measured at time t_1 : EOU₁, U₁, Gender, and Age. Variables measured at time t_2 : EOU₂, U₂, Use.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Copyright: INFORMS holds copyright to this *Articles in Advance* version, which is made available to subscribers. The file may not be posted on any other website, including the author's site. Please send any questions regarding this policy to permissions@informs.org.

low experiences and high experiences, moderate disconfirmation would occur only at extreme level of expectations—i.e., low expectations and high expectations, respectively. Although Figure 2 might suggest that H1 is not supported for these extreme cases, we do not test them because of lack of statistical tests for such extreme cases.

H2 suggests that positive disconfirmation (experience > expectation) will have a positive effect on use and negative disconfirmation (experience < expectation) will have a negative effect on use. As shown in Figure 2, a high magnitude of negative disconfirmation is represented by low experience ($U_1 = -3$) and high expectation ($U_2 = -3$), whereas a high magnitude of positive disconfirmation is represented by high experience ($U_1 = 3$) and low expectation ($U_2 = 3$). H2 also suggests that the increase in use associated with positive disconfirmation is smaller than the decrease in use associated with negative disconfirmation. To test this hypothesis, we examined the slopes for positive and negative disconfirmation. Support for this hypothesis would require the slope for negative disconfirmation to be greater than the slope for positive disconfirmation. For this, we examined two cubic equations: one with low experience (for negative disconfirmation) and the other with high experience (for positive disconfirmation). A significant difference in linear slopes for these cubic equations would provide support for H2 (as is the case with other non-parametric tests, jackknifing was used for calculating significance level). As shown in Figure 2, we found that the decrease in level of use for negative disconfirmation was greater than the increase in use for positive disconfirmation. Further, a significant difference in the slope of the surface along the positive and negative disconfirmation axes indicated that H2 was strongly supported ($a_{y(\text{negative disconfirmation})} =$

$a_{y(\text{positive disconfirmation})} = 2.14; p < 0.01$). Next, we conduct further tests to provide additional support for our hypotheses using response surface analysis (Edwards 2001).

4.3. Response Surface Analysis

The significant higher-order terms (e.g., $U_1U_2^2$) in the unconstrained regression equation, shown in Table 2, indicated that the relationship between usefulness and use is curvilinear. Therefore, in order to provide additional support for our hypotheses, we conducted response surface analysis to determine the exact nature of the relationship between usefulness and use. The response surface depicted by perceived usefulness predicting use is shown in Figure 3.

As noted earlier, H1 and H2 were supported if the cubic slope of the surface along the disconfirmation (a_y^3) axis was significant and positive (test 1). The cubic slope of the surface along the disconfirmation axis ($a_y^3 = 1.49, p < 0.01$) was found to be positive and significant, thus providing additional support for H1 and H2. Also, the linear slope along the confirmation axis ($a_x = 1.68; p < 0.01$) was significant and positive (test 2). The curvilinear slope (quadratic slope $a_x^2 = 0.10; p < 0.01$; cubic slope $a_x^3 = -0.17; p < 0.01$) along the confirmation axis, although close to zero, was significant (tests 3 and 4), providing only weak support for the proposed model. The notion of weak support (coefficients lower than 0.20) is also referred to as being not practically significant. Likewise, for slopes that are very close to, but not exactly the same as, the desired value—as in the range we observe

Figure 2 Plot for Predicting Technology Use Using Perceived Usefulness

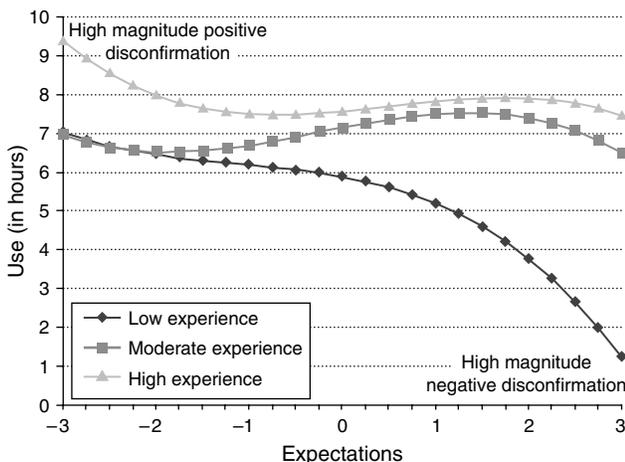
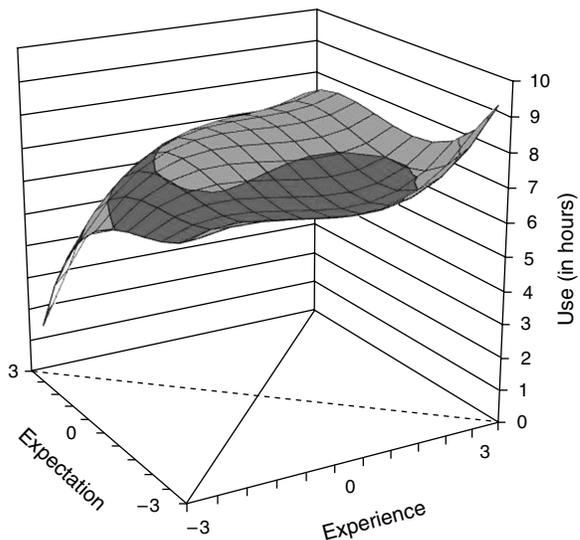


Figure 3 Response Surface for Perceived Usefulness Predicting Use



Note. The solid line running diagonally from the near corner to the far corner represents the confirmation axis (experiences = expectations), and the dotted line diagonally left to right represents the disconfirmation line (experiences = -expectations).

here—Edwards claims that they are not sufficiently different, despite significant p -values (e.g., Edwards 2002, Edwards and Parry 1993). Overall, this response surface has three key features: (1) the relationship between usefulness and use is curvilinear such that for a high magnitude of disconfirmation, use is driven by the level and direction of disconfirmation, and for a low magnitude of disconfirmation, use is driven by the level of expectations; (2) the level of use was highest for high-magnitude positive disconfirmation and lowest for high-magnitude negative disconfirmation; and (3) decrease in use for the negative disconfirmation is higher than the increase in use for the positive disconfirmation, indicating that losses loom large than gains.

5. Discussion

This study proposed a new model that outlined possible complex interactions between expectations and experiences in determining a key outcome—i.e., technology use—by integrating the assimilation-contrast model and prospect theory. We tested the proposed model in a longitudinal field study that used survey data about expectations and experiences and use data from system logs. We tested linear, quadratic, and cubic models, and found that the cubic model explained as much as 70% of the variance in use. In the remainder of this section, we discuss theoretical and practical implications.

5.1. Theoretical Implications

Our work sought to make contributions to expectation confirmation research, particularly in IS, by drawing from domain-independent work on expectation confirmation—i.e., assimilation-contrast model and prospect theory—and the domain-specific model in TAM. Further, we emphasized the roles of expectations and experiences of perceived usefulness in influencing technology use, thus providing a more central role for the IS context in our theorizing (see Agarwal and Lucas 2005). In doing so, we explained technology use as a function of both the assimilation-contrast model and prospect theory. This is one of the first studies in the IS literature to minimize the analytical limitations of prior expectation confirmation research. Clearly, the results provide support for the complexity of the interaction between experiences and expectations in predicting a key outcome—here, technology use. The results highlight some very important considerations for future research. Specifically, by relaxing the linearity assumption, we demonstrated that there is a curvilinear relationship among the variables of interest, as posited by Staples and Seddon (2005).

Expectation confirmation research, as we noted earlier, is always conducted in a particular context. Here, we studied technology use as the dependent variable

and used perceived usefulness as the primary predictor, while controlling for ease of use and other control variables. By extending the widely used TAM to the context of expectation confirmation research, our work makes a contribution to this mature area. It is interesting to note that our model, which employs one predictor—i.e., usefulness—and its variants—i.e., expectations, experiences, and mathematically calculated terms—is able to account for as much as 70% of the variance in technology use, albeit with the inclusion of a few control variables. This compares well to the majority of research explaining technology use, where the variance explained has typically been 50% or less. The variance explained also compares favorably to work that uses models employing a much larger number of unique constructs, such as innovation diffusion theory or unified theory of acceptance and use of technology. However, those studies are typically explaining another perception variable, such as intention, rather than actual behavior, which is our focus here. Although the predictive validity of our model suggests it is a contribution to the literature explaining technology use, future work should compare the current model with other models of technology use.

The results of this research provide another data point demonstrating the power of polynomial modeling for understanding IS phenomena. These results provide evidence that studying IS acceptance from a linear perspective alone may yield limited or even inaccurate understanding of the phenomenon. Thus, drawing on the viewpoint of Edwards (e.g., Edwards 1994a), IS researchers should consider nonlinear models when examining issues of fit or congruence. In general, polynomial modeling will identify a linear relationship only when one truly exists. Even though Edwards and others have examined (and even re-examined) many phenomena using polynomial models, we are not aware of any examinations of cubic models. We thus extend the work of Edwards and his colleagues by providing assessments of the cubic model. Specifically, the analytical representation and tests provided here can allow researchers in IS and organizational behavior to examine cubic models.

Although a number of studies have demonstrated the appropriateness of polynomial models in a variety of contexts (e.g., Edwards 1994a, b; Edwards and Harrison 1993; Edwards and Parry 1993; Edwards and Rothbard 1999; Kristof-Brown and Stevens 2001), this is one of the first such studies in the domain of IS (cf. Venkatesh and Goyal 2010). Many areas of organizational research examine expectations and actual evaluations—e.g., negotiation (Barry and Oliver 1996, Oliver et al. 1994), person-job fit (Saks and Ashforth 1997), and person-organization fit (Cable and Judge 1996, Kristof 1996). Others suggest an examination

of desires and actual evaluations (e.g., Spreng et al. 1996). Still other research relies on difference scores or individuals' estimates of expectation-actual fit (e.g., Bhattacharjee 2001, Bhattacharjee and Premkumar 2004, Patterson 1993). In all cases, the goal of the research is to understand the impact of *fit* or *congruence* on some outcome. The use of polynomial models to understand these phenomena will enrich our understanding of the role of key predictors and the complexity of their influence on outcomes.

The support for the proposed model offers two important contributions to IS research. We are aware of no prior work on expectation confirmation that adopts an integrated view of the assimilation-contrast model and prospect theory. Indeed, we are aware of no research in IS that has leveraged the assimilation-contrast model. However, our results demonstrated that the proposed model provides a good explanation of the relationship among expectations, experiences, and use of a new technology. The unique advantage of this model is that it accounts for direction and magnitude of disconfirmation, suggesting that small differences have an almost inconsequential effect. Although theorizing about how and why the assimilation-contrast model will be applicable to the technology use context alone represents an important step in advancing our understanding of technology use, by integrating prospect theory also, we present an entirely new model that suggests a new way of thinking about expectation confirmation research in general and in the context of technology use in particular. Beyond the magnitude of disconfirmation for which assimilation-contrast model accounts, our model accounts for the direction of the deviation, treating positive and negative disconfirmation differently. Thus, our model provides insights into *how* disconfirmation influences technology use.

5.2. Limitations and Future Research

Like most empirical research, our study was not without limitations. Polynomial modeling, the data analysis approach we used for this study, is based on the assumption of standard regression that the independent variables are measured without error. As the reliabilities of the component measures (here, expected and experienced usefulness) decrease, coefficient estimates may be biased (Edwards 2002). This effect is even more pronounced for higher-order terms (Edwards and Harrison 1993). Because all the measurement scales showed high reliability ($\alpha > 0.80$), we do not expect this limitation to have much of an impact on the findings. Further, polynomial modeling primarily applies to congruence between two independent variables (here, expected and experienced usefulness) as predictors of an outcome variable (here, use). As noted earlier, prior research (e.g., Venkatesh

et al. 2003) has shown usefulness as the only consistent direct predictor of intention and use behavior. Therefore, our focus on expectations and experiences associated with usefulness, with ease of use as control variable, is not much of a limitation, although future work should certainly investigate more comprehensive models based on the encouraging findings when using polynomial modeling in this work.

The model developed here has the potential to be applicable in the contexts of other behaviors. However, given that the theory development focused on the IS context, relevant beliefs, and technology use as the dependent variable, only future research that focuses on the generalizability of our model to other behaviors can shed light on this issue. Consistent with prior technology adoption literature, we operationalized use by measuring duration of technology use from the system logs. However, there are other measures of use—e.g., extent and intensity of use—that have been used in the literature (e.g., Davis et al. 1989). Therefore, another research direction will be to test the generalizability of our model by using these other measures of use.

The six-month interval between measurements of expectations and experiences is a potential strength and weakness. It is a strength in that the measure of experience likely reflects a somewhat steady-state assessment after the shakedown. However, it raises some questions regarding potential biases and additional, unaccounted for, factors. For example, an information-processing perspective (Hogan 1987) suggests that raters may overweight negative information in order to reduce uncertainty resulting in ratings lower than warranted. In establishing this interval, we had to make a trade-off—specifically, we considered the potential for biases and the need to clearly separate measures of expectations and experiences. In addition, we needed to limit interference with the organization's implementation process. In moving this line of inquiry forward, alternative measurement intervals and techniques should be considered.

There are many important future research directions worth considering that will help identify critical contingencies. Identifying appropriate contingencies is essential before drawing conclusions regarding the generalizability of our model. In our study, individual differences were not explicitly modeled. It is possible that different types of individuals—i.e., different personality profiles—could react differently, thus resulting in personality playing a key moderating role. Further, the measurement of expectations may have built-in biases that require further study. For instance, some individuals may set their own expectations low in order to avoid being disappointed, whereas others may be more optimistic and

expect the best. Similarly, in our study, employees' specific levels of fit with their job or organization were not modeled or controlled. Once again, it is possible that such variables could serve as moderators.

As noted earlier, this is one of the first studies in IS to use polynomial modeling. Like technology acceptance research, research in most other areas has focused on linear effects. It is thus likely that other research areas can also benefit from the use of polynomial modeling. We provide two such illustrations. For instance, much prior research in team diversity has shown conflicting findings. Although some research has shown a positive relationship between team diversity and team performance (e.g., Richard 2000), others have found a negative relationship (e.g., Reagans et al. 2004). Polynomial modeling has the potential to inform this research stream because recent studies (e.g., Knippenberg and Schippers 2007) have called for examination of curvilinear relationships to address these inconsistencies. Trust in technology is another research stream that has the potential to benefit from the use of polynomial modeling. This research stream has predominantly employed linear relationships to examine influence of trust. Some research in the marketing literature (e.g., Agustin and Singh 2005) has shown that trust can have curvilinear influence on the variables, such as loyalty intentions and IS research would benefit from such an investigation.

5.3. Practical Implications

From a practical perspective, the results of this research suggest that the impact of expectations on technology use is significant. The key thing to note is the importance of organizations setting accurate expectations. The integrated model that we propose suggests that negative disconfirmation has far greater negative consequences than positive disconfirmation has positive consequences. Thus, the key take-away for practice is to aim for setting realistic expectations. However, if there is a possibility for a large deviation between expectations and actual experiences, it will be best to err on the side of setting expectations low to avoid large negative consequences for failing to meet them.

Our research focused on use after six months of employee experience with the system. Further, in predicting use in the second six months after implementation, we employed preimplementation expectations and postimplementation experiences in our model, in addition to controlling for use in the first six months. In contrast to much prior research that, perhaps for practical reasons, has typically examined use only for a short duration following the implementation (e.g., Davis and Venkatesh 2004), our work helps managers understand use after the shake-down phase has passed and at least a semblance

of a steady state has been achieved (see Morris and Venkatesh 2010). Our results suggest that managers should carefully consider both expectations and experiences of usefulness and their complex interactions in understanding steady state technology use. Measuring key beliefs, e.g., usefulness expectations alone, such as what can be inferred from Davis and Venkatesh (2004), or usefulness experiences alone, such as what is suggested in the extant technology acceptance research, may not provide an accurate or complete understanding of long-term use. Instead, we emphasize the need for managers to measure expectations and experiences, and that too temporally separated, in order to best predict long-term technology use. The prediction of our model is likely to be far more accurate than simpler models, thus allowing managers to take corrective action, if necessary, or to abandon a failing project. Although we realize that managers may not necessarily be able to use polynomial modeling or the response surface methodology, these methodologies could be implemented in a decision support tool that managers could readily and easily use.

At the outset, we noted that employees often anticipate that systems will fall short of expectations in some ways. However, this work clearly points to the danger in allowing those anticipations to prevail. If vendors and designers were to make extravagant promises with the goal of slowly adjusting experiences downward in hopes that users may forget their initial expectations, our research suggests that that would not happen and the consequences (outcomes) of such low experiences (paired with high expectations) could be disastrous. Vendors and even internal IT organizations use training as a way to educate users about the system. Such training sessions frequently provide an opportunity to create hype about the system to draw in the users. Yet again, in this regard, our findings would advocate against such a strategy. Rather, the system, its scope, its functionalities, its procedural details, amount of learning effort needed, and limitations should be clearly and accurately described in order to positively impact expectation confirmation and subsequent technology use.

6. Conclusions

This research examined the relationship among expectations, experiences, and the outcome of technology use. The objective was to understand the discrepancies in prior expectations research in IS. Specifically, we proposed a theoretical model, integrating the assimilation-contrast model and prospect theory, to explain the relationship between expectations, experiences, and use, and tested the model using polynomial modeling. The results support the proposed

model. This work provides key insights into the role of expectations and experiences in technology use, with a polynomial model being supported.

References

- Agarwal, R., H. Lucas. 2005. The information systems identity crisis: Focusing on high-visibility and high-impact research. *MIS Quart.* **29**(3) 381–398.
- Agarwal, R., J. Prasad. 1998. A conceptual and operational definition of personal innovativeness in the domain of information technology. *Inform. Systems Res.* **9**(2) 204–215.
- Agustin, C., J. Singh. 2005. Curvilinear effects of consumer loyalty determinants in relational exchanges. *J. Marketing Res.* **42**(1) 96–108.
- Ajzen, I. 1991. The theory of planned behavior. *Organ. Behav. Human Decision Processes* **50**(2) 179–211.
- Anderson, R. E. 1973. Consumer dissatisfaction: The effect of disconfirmed expectancy on perceived product performance. *J. Marketing Res.* **10**(1) 38–44.
- Anderson, E. W., M. W. Sullivan. 1993. The antecedents and consequences of customer satisfaction for firms. *Marketing Sci.* **12**(2) 125–143.
- Barry, B., R. L. Oliver. 1996. Affect in dyadic negotiation: A model and propositions. *Organ. Behav. Human Decision Processes* **67**(2) 127–143.
- Bearden, W. O., J. E. Teel. 1983. Selected determinants of consumer satisfaction and complaint reports. *J. Marketing Res.* **20**(1) 21–28.
- Berry, L. L., A. Parasuraman. 1991. *Marketing Services: Competing Through Quality*. Free Press, New York.
- Bhattacharjee, A. 2001. Understanding information systems continuance: An expectation-confirmation model. *MIS Quart.* **25**(3) 351–370.
- Bhattacharjee, A., G. Premkumar. 2004. Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quart.* **28**(2) 229–254.
- Bollen, K. A., R. Jackman. 1990. Regression diagnostics: An expository treatment of outliers and influential cases. J. Fox, J. Scottlong, ed. *Modern Methods of Data Analysis*. Sage, Newbury Park, CA, 257–291.
- Boudreau, M. C., D. Robey. 2005. Enacting integrated information technology: A human agency perspective. *Organ. Sci.* **16**(1) 3–18.
- Boulding, W., A. Kalra, R. Staelin, V. A. Zeithaml. 1993. A dynamic process model of service quality: From expectations to behavioral intentions. *J. Marketing Res.* **30**(1) 7–27.
- Brown, S. A., V. Venkatesh, J. N. Kuruzovich, A. P. Massey. 2008. Expectation confirmation: An examination of three competing models. *Organ. Behav. Human Decision Processes* **105**(1) 52–66.
- Cable, D. M., T. A. Judge. 1996. Person—Organization fit, job choice decisions, and organizational entry. *Organ. Behav. Human Decision Processes* **67**(3) 294–311.
- Caligiuri, P., J. Phillips, M. Lazarova, I. Tarique, P. Burgi. 2001. The theory of met expectations applied to expatriate adjustment: The role of crosscultural training. *Internat. J. Human Resource Management* **12**(3) 357–372.
- Churchill, Jr., G. A., C. Surprenant. 1982. An investigation into the determinants of customer satisfaction. *J. Marketing Res.* **19**(4) 491–504.
- Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quart.* **13**(3) 319–340.
- Davis, F. D., V. Venkatesh. 2004. Toward preprototype user acceptance testing of new information systems: Implications for software project management. *IEEE Trans. Engrg. Management* **51**(1) 31–46.
- Davis, F. D., R. P. Bagozzi, P. R. Warshaw. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Sci.* **35**(8) 982–1003.
- DeLone, W. H., E. R. McLean. 1992. Information systems success: The quest for the dependent variable. *Inform. Systems Res.* **3**(1) 60–95.
- DeLone, W. H., E. R. McLean. 2003. The DeLone and McLean model of information systems success: A ten-year update. *J. Management Inform. Systems* **19**(4) 9–30.
- Edwards, J. R. 1994a. The study of congruence in organizational behavior research: Critique and a proposed alternative. *Organ. Behav. Human Decision Processes* **58**(1) 51–100.
- Edwards, J. R. 1994b. Regression analysis as an alternative to difference scores. *J. Management* **20**(3) 683–689.
- Edwards, J. R. 1995. Alternatives to difference scores as dependent variables in the study of congruence in organizational research. *Organ. Behav. Human Decision Processes* **64**(3) 307–324.
- Edwards, J. R. 2001. Ten difference score myths. *Organ. Res. Methods* **4**(3) 265–287.
- Edwards, J. R. 2002. Alternatives to difference scores: Polynomial regression analysis and response surface methodology. F. Drasgow, N. Schmidt, eds. *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis*. Jossey-Bass/Pfeiffer, San Francisco, 350–400.
- Edwards, J. R., C. L. Cooper. 1990. The person-environment fit approach to stress: Recurring problems and some suggested solutions. *J. Organ. Behav.* **11**(4) 293–307.
- Edwards, J. R., R. V. Harrison. 1993. Job demands and worker health: Three-dimensional reexamination of the relationship between person-environment fit and strain. *J. Appl. Psych.* **78**(4) 628–648.
- Edwards, J. R., M. E. Parry. 1993. On the use of polynomial regression equations as an alternative to difference scores in organizational research. *Acad. Management J.* **36**(6) 1577–1613.
- Edwards, J. R., N. P. Rothbard. 1999. Work and family stress and well-being: An examination of person-environment fit in the work and family domains. *Organ. Behav. Human Decision Processes* **77**(2) 85–129.
- Festinger, L. 1962. *A Theory of Cognitive Dissonance*. Stanford University Press, Stanford, CA.
- Ginzberg, M. J. 1981. Early diagnosis of MIS implementation failure: Promising results and unanswered questions. *Management Sci.* **27**(4) 459–478.
- Hogan, E. A. 1987. Effects of prior expectations on performance ratings: A longitudinal study. *Acad. Management J.* **30**(2) 354–368.
- Irving, P. G., J. P. Meyer. 1994. Reexamination of the met-expectations hypothesis: A longitudinal analysis. *J. Appl. Psych.* **79**(6) 937–949.
- Jasperson, J., P. E. Carter, R. W. Zmud. 2005. A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quart.* **29**(3) 525–557.
- Johnston, R. 1995. The zone of tolerance: Exploring the relationship between service transactions and satisfaction with the overall service. *Internat. J. Service Industry Management* **6**(2) 46–61.
- Kahneman, D., A. Tversky. 1979. Intuitive prediction: Biases and corrective procedures. *Management Sci.* **12** 313–327.
- Kahneman, D., A. Tversky. 1984. Choice, values, and frames. *Amer. Psych.* **39**(4) 341–350.
- Kennedy, J. R., P. C. Thirkell. 1988. An extended perspective on the antecedents of satisfaction. *J. Consumer Satisfaction, Dissatisfaction Complaining Behav.* **1**(1) 2–9.

- Kim, S. S., N. K. Malhotra. 2005. A longitudinal model of continued use: An integrative view of four mechanisms underlying post-adoption phenomena. *Management Sci.* **51**(5) 741–755.
- Klein, J. G. 1999. Developing negatives: Expectancy assimilation and contrast in product judgments. *Adv. Consumer Res.* **26**(1) 463–468.
- Knippenberg, D. V., M. C. Schippers. 2007. Work group diversity. *Annual Rev. Psych.* **58**(2) 515–541.
- Kristof, A. L. 1996. Person-organization fit: An integrative review of its conceptualizations, measurement, and implications. *Personnel Psych.* **49**(1) 1–49.
- Kristof-Brown, A. L., C. K. Stevens. 2001. Goal congruence in project teams: Does the fit between members' personal mastery and performance goals matter? *J. Appl. Psych.* **86**(6) 1083–1095.
- Liljander, V., T. Strandvik. 1993. Estimating zones of tolerance in perceived service quality and perceived service value. *Internat. J. Service Indust. Management* **4**(2) 6–28.
- Limayem, M., S. G. Hirt, C. M. K. Cheung. 2007. How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quart.* **31**(4) 705–737.
- McAfee, A. 2003. When too much IT knowledge is a dangerous thing. *MIT Sloan Management Rev.* **44**(2) 83–89.
- McElroy, J. C., P. C. Morrow, E. J. Mullen. 1996. Intraorganizational mobility and work related attitudes. *J. Organ. Behav.* **17**(4) 363–374.
- Morris, M. G., V. Venkatesh. 2010. Job characteristics and job satisfaction: Understanding the role of enterprise resource planning system implementation. *MIS Quart.* **34**(1) 143–161.
- Oliver, R. L. 1977. Effect of expectation and disconfirmation on post-exposure product evaluations: An alternative interpretation. *J. Appl. Psych.* **62**(4) 480–486.
- Oliver, R. L. 1980. A cognitive model of the antecedents and consequences of satisfaction decisions. *J. Marketing Res.* **17**(4) 460–469.
- Oliver, R. L., P. V. S. Balakrishnan, B. Barry. 1994. Outcome satisfaction in negotiation: A test of expectancy disconfirmation. *Organ. Behav. Human Decision Processes* **60**(2) 252–275.
- Ong, C. S., J. Y. Lai. 2006. Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Comput. Human Behav.* **22**(5) 816–829.
- Patterson, P. G. 1993. Expectations and product performance as determinants of satisfaction for a high-involvement purchase. *Psych. Marketing* **10**(5) 449–465.
- Patterson, P. G., M. Cicic, A. Shoham. 1997. A temporal sequence model of satisfaction and export intentions of service firms. *J. Global Marketing* **10**(4) 23–43.
- Podsakoff, P. M., D. W. Organ. 1986. Self-reports in organizational research: Problems and prospects. *J. Management* **12**(4) 531–544.
- Prewitt, E., L. C. Ware. 2006. The state of the CIO "06." Last accessed January 24, 2008, <http://www.cio.com/archive/010106/JAN1SOC.pdf>.
- Reagans, R., E. Zuckerman, B. McEvily. 2004. How to make the team: Social networks vs. demography as criteria for designing effective teams. *Admin. Sci. Quart.* **49**(1) 101–133.
- Richard, O. C. 2000. Racial diversity, business strategy, and firm performance: A resource-based view. *Acad. Management J.* **43**(2) 164–177.
- Saks, A. M., B. E. Ashforth. 1997. A longitudinal investigation of the relationships between job information sources, applicant perceptions of fit, and work outcomes. *Personnel Psych.* **50**(2) 395–426.
- Sprengh, R. A., S. B. MacKenzie, R. W. Olshavsky. 1996. A reexamination of the determinants of consumer satisfaction. *J. Marketing* **60**(3) 15–32.
- Staples, D. S., P. Seddon. 2005. Testing the technology-to-performance chain model. *Advanced Topics in Organizational and End User Computing*. Idea Group Publishing, Hershey, PA, 42–64.
- Staples, D. S., I. Wong, P. B. Seddon. 2002. Having expectations of information systems benefits that match received benefits: Does it really matter? *Inform. Management* **40**(2) 115–131.
- Straub, D., M. Limayem, E. Karahanna-Evaristo. 1995. Measuring system usage: Implications for IS theory testing. *Management Sci.* **41**(8) 1328–1342.
- Szajna, B., R. W. Scamell. 1993. The effects of information system user expectations on their performance and perceptions. *MIS Quart.* **17**(4) 493–516.
- Szymanski, D. M., D. H. Henard. 2000. E-satisfaction: An initial examination. *J. Retailing* **76**(3) 309–322.
- Tversky, A., D. Kahneman. 1991. Loss aversion in riskless choice: A reference-dependent model. *Quart. J. Econom.* **106**(4) 1039–1061.
- Tversky, A., D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertainty* **5**(4) 297–323.
- Venkatesh, V., F. D. Davis. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Sci.* **46**(2) 186–204.
- Venkatesh, V., S. Goyal. 2010. Expectation disconfirmation and technology adoption: Polynomial modeling and response surface analysis. *MIS Quart.* **34**(2) 281–303.
- Venkatesh, V., M. G. Morris, G. B. Davis, F. D. Davis. 2003. User acceptance of information technology: Toward a unified view. *MIS Quart.* **27**(3) 425–478.
- Yi, Y. 1990. A critical review of consumer satisfaction. V. A. Zeithaml, ed. *Review of Marketing*. American Marketing Association, Chicago, 68–123.