Expectation Confirmation in Technology Adoption:

An Examination of Six Competing Theoretical Models

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ABSTRACT

We discuss six different models of expectation confirmation: assimilation, contrast, generalized negativity, assimilation-contrast, experiences only, and expectations only. We identified four shortcomings of prior empirical research on expectation confirmation in IS and other fields: reliance on a single model, assumption of linearity, use of difference scores, and direct measures. Using constructs from the widely studied technology acceptance model (TAM), we test each of these six models, which suggest different roles for expectations and experiences, using expectations and experiences about ease of use and usefulness as predictors of behavioral intention. 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 expectations and experiences have differential impacts on intention depending on whether we are examining ease of use or usefulness. Specifically, the results did not support any of the existing models of expectation confirmation but rather, we present a modified generalized negativity and contrast model.

INTRODUCTION

Competing models of expectation confirmation, with different underlying theoretical explanations, have been put forth in organizational behavior, marketing, and psychology. Among the various models, four overarching models examining expectations, experiences, and consequent outcomes have received a great deal of attention: assimilation, contrast, generalized negativity, and assimilation-contrast (Anderson 1973; Klein 1999; Oliver 1977, 1980; Yi 1999). In addition, models hypothesizing no role for expectations or experiences—i.e., experiences only and expectations only—have emerged (e.g., Hom et al. 1999; Irving and Meyer 1994; Pulakos and Schmitt 1983). Each model varies in terms of its prescriptions on how expectations should be set in order to produce desirable outcomes. Thus, the goal of expectation confirmation research is to understand how missing, meeting, or exceeding expectations influences the acceptance of an information system (or the ultimate outcome of interest). Prior organizational behavior research has examined these models in a variety of contexts, such as organizational commitment (Wanous et al. 1992), job satisfaction (Greenhaus et al. 1983), and intention to turnover (Wanous et al., 1992). There is also a long history of research on expectations and its ties to IS outcomes (e.g., Bhattacharjee 2001; Ginzberg 1981; Staples et al. 2002; Szajna and Scamell 1993). IS research draws from organizational behavior and psychology (e.g., Churchill and Suprenant 1982; Festinger 1962; Oliver 1980), although none of the four models that we mentioned initially have been explicitly examined.
There are a few important gaps in the expectations confirmation research, both in IS and the reference disciplines, that merit attention. Much of the research on expectation confirmation, both in IS and reference disciplines, has typically chosen a single theoretical perspective and empirically tested the model in a particular context (e.g., product, job). While the use of a single theoretical model is valuable, as research in a particular area progresses, it is important to compare different models in a single study to identify the best model or to allow for an integrated model to emerge (e.g., Taylor and Todd 1995; Keil et al. 2000). As Poole and Van de Ven (1989) propose, leveraging the tensions associated with the differences in the models can “stimulate the development of more encompassing theories” (p. 563). Also, testing the predictive validity of different theoretical models in a single empirical study is perhaps the only way to get the most accurate comparison of the relative predictive validity of the models (e.g., Keil et al. 2000).

Beyond the use of single models, there are three main problematic assumptions and methodological gaps in prior empirical research on expectation confirmation that should be noted. First, prior empirical research on expectation disconfirmation has relied mostly on linear models (e.g., Boulding et al. 1993; Churchill and Suprenant 1982). However, some researchers have argued that linear models fail to adequately capture the complexity associated with the relationship among expectation, experience, and outcome variable (Edwards and Parry 1993). Also, non-linear effects have been found in prior IS research (e.g., Brown and Venkatesh 2005; Rai et al. 1998). Second, a number of studies have used difference scores to determine the level of disconfirmation of expectations (e.g., French et al. 1982). Management, organization behavior, and personnel psychology literatures have highlighted a number of problems associated with the use of difference scores (Edwards 2002; Edwards and Harrison 1993; Irving and Meyer 1995). Third, recent studies have used direct measurement of disconfirmation in order to circumvent any problems associated with the difference scores (Bhattacherjee 2001; Bhattacherjee and Premkumar 2004). Direct measurement is also known to have problems such as recall bias (Irving and Meyer 1994, 1995, 1999).
Given this backdrop, the basic objective of this research is to review and empirically examine the six different models of expectation confirmation in the context of an information systems implementation. Specifically, we use the technology acceptance model (TAM; Davis et al. 1989) to identify the constructs about which user expectations, experiences, and outcomes will be assessed. We examine expectations and experiences related to perceived usefulness and perceived ease of use, the two key predictors in TAM, and the outcome of intention to continue using a system. The vast body of research on TAM has typically examined intention as a linear function of both perceived usefulness and perceived ease of use. Further, in most cases, either expectations (pre-use beliefs) or experiences (post-use beliefs) are used as predictors of intention (see for examples, Straub et al. 1995; Venkatesh 1999) but seldom have they been examined in a single model (cf. Szjana and Scamell 1993). We overcome the various limitations and address the gaps in the prior research by treating expectations and experiences separately, and using polynomial modeling to test the six models of expectation confirmation (see Edwards 1995; Edwards and Harrison 1993; Edwards and Parry 1993). We also use response surface analysis to gain a visual understanding regarding which of the six models of expectation confirmation is best supported in the context of TAM.

TECHNOLOGY ACCEPTANCE

TAM has been the focus of several studies that examine individuals’ beliefs and intention to use information systems. TAM employs perceived ease of use and usefulness as the determinants of intention that in turn determines use behavior. 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—system 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 (e.g., consumer products, jobs, information systems).
MODELS OF EXPECTATION CONFIRMATION

As noted earlier, the four dominant models of expectation confirmation are: assimilation, contrast, generalized negativity, and assimilation-contrast (Anderson 1973). In addition, two other models are: experiences only and expectations only. In essence, each model examines the impact of some combination of expectations and experiences on an outcome. In this section, we first discuss the models and their predictions; next, we discuss prior empirical results related to the different models; and, finally, we discuss the key methodological and analytical limitations of prior expectations confirmation research.

Assimilation Model

Based on cognitive dissonance and assimilation theories (Festinger 1962; Hovland et al. 1957), the assimilation model suggests that a priori expectations provide an anchor for outcome evaluations such that the higher one’s expectations, the higher the subsequent evaluations (Sherif and Sherif 1967). In an assimilation model, actual experiences provide input to outcome evaluations but the outcome evaluations are biased in favor of the expectations. This view argues that deviations from one’s expectations create dissonance, which is an uncomfortable state. In order to reduce dissonance, subsequent outcome evaluations are adjusted—i.e., assimilated—to be more consistent with expectations. In essence, a priori expectations provide an anchor for outcome evaluations such that the higher one’s expectations, the higher the subsequent evaluations (Sherif and Sherif 1967). Individuals minimize the cognitive difference between expectations and outcomes by adjusting outcome evaluations to be more consistent with expectations, thus reducing dissonance. The assimilation view suggests that outcomes should be overstated in hopes of raising expectations. These higher expectations would lead individuals to adjust their perceptions in a positive manner in order to reduce dissonance. This would then result in more positive outcomes.

Support for the assimilation model can be found in a number of domains. In a study examining service quality perceptions, Boulding et al. (1993) found that by increasing customer expectations of product quality, overall quality evaluations increased, thus supporting an assimilation model. Researchers
have found similar results with respect to consumer expectations, perceptions, and product evaluation (Hoch and Ha 1986; Olshavsky and Miller 1972; Olson and Dover 1979). Research on employee expectations, experiences, and overall job satisfaction has also found similar results (e.g., Hoiberg and Berry 1978; Ilgen 1971). Finally, Szajna and Scamell (1993) examined the relationship among expectations regarding an information system, its actual performance, and satisfaction with the system. Their experimental design incorporated manipulations of expectations regarding a system. The results indicated that participants in the ‘high expectation’ treatment had the highest satisfaction levels, although all participants used the same system, thus providing evidence in support of an assimilation model.

**Contrast Model**

A contrast model, with its roots in disconfirmation and contrast theories (Churchill and Suprenant 1982; Sherif and Hovland 1961), suggests that ultimate outcome evaluations are based on the direction and size of the gap between expectations and experiences, and ultimately biased in the direction of experiences. Rather than focus on the expectations, as in assimilation theory, disconfirmation theory focuses on the difference between the expectations and the subsequent evaluations. Under this view, high positive disconfirmation (i.e., the degree to which expectations are exceeded) leads to greater satisfaction while high negative disconfirmation (i.e., the degree to which expectations are unmet) leads to lower satisfaction (Kopalle and Lehman 2001; for a review, see Yi 1990). Thus, the contrast model offers management recommendations that are opposite to what would be suggested by the assimilation view and suggests that potential outcomes should be understated in order to maximize the expectation-outcome gap in the positive direction—i.e., the degree to which experiences exceed expectations.

The stream of research most consistent with the contrast model is in realistic job previews (e.g., Philips 1998; Wanous 1992). The primary proposition of this research is that when employees have realistic job previews, that is their expectations more closely align with the job conditions they will encounter, they are more likely to have their expectations met or exceeded, and will thus be more satisfied.
and less likely to leave their jobs (Dugoni and Ilgen 1981; Lee et al. 1992; Wanous 1992). Kotter (1973) suggested that unrealistically high expectations lead to significant negative outcomes such as turnover, low satisfaction, and lack of organizational commitment. Realistic job preview research proposes that lowered expectations should reduce the resulting dissatisfaction that newcomers experience (Wanous 1992). There is some empirical support for the contrast model in IS research as well. Staples et al. (2002) found that individuals with unrealistically high expectations had lower perceptions of information system effectiveness and satisfaction, when compared to those with accurate or high perceptions.

**Generalized Negativity**

The third view, *generalized negativity*, has its roots in met expectations research (Porter and Steers 1973). The generalized negativity view proposes that any difference between expectations and experiences results in a lowered outcome evaluation, regardless of whether that difference is positive (i.e., expectations are exceeded) or negative (i.e., expectations are unmet) (Olson and Dover 1979). While a negative impact associated with having expectations exceeded is not intuitively appealing, it is supported in equity theory (Adams 1963). Equity theory suggests that getting more than one expects, or perceives to be fair, results in dissatisfaction due to the psychological tension created by the mismatch. According to Santos and Boote (2003), there is a hierarchy of anticipations such that people actually expect less than they want or desire. This hierarchy provides conceptual support for the negative impact of large positive deviations. In sum, a generalized negativity view would argue for setting expectations accurately to eliminate any deviation and minimize psychological tension thus, maximizing satisfaction.

The *generalized negativity* model suggests that the direction of discrepancy does not matter, rather any difference between expectations and experience is bad. This is supported in research by Rice et al. (1989) who examined the impact of discrepancies between wants and experiences on satisfaction. While not focused on expectations, the Rice et al. results support the notion that getting more than you want can have a negative impact. It seems reasonable that this impact would translate to expectations, as well. In a
study of information systems implementation, Ginzberg (1981) demonstrated that users who held realistic expectations were more satisfied with the resulting information system than were users with unrealistic expectations. Likewise, Bhattacherjee (2001)’s study of information system use in electronic commerce found a positive relationship between met expectations and information system satisfaction.

**Assimilation-contrast**

The *assimilation-contrast model*, with its roots in both the assimilation and contrast models discussed earlier (see Anderson 1973), proposes that for slight differences, outcome evaluations will assimilate toward expectations, while large differences, due to the magnitude of their contrast, will be weighted more heavily (e.g., Klein 1999). 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 consistent with expectations, as in the assimilation model (Festinger 1962; Hovland et al. 1957)—i.e., expectations create inertia in which outcomes are consistent with expectations as long experiences are not outside of a set range (Liljander and Strandvik 1993). As the difference between expectations and experiences increases, individual experiences lead to either a disappointment effect—i.e., experiences fall short of expectations—or a surprise effect—i.e., experiences exceed expectations (Coughlan and Connolly 2001), consistent with the contrast model. Prospect theory (Kahneman and Tversky 1979) suggests that negative disconfirmation will have a greater negative impact on outcome evaluations than positive disconfirmation will have in the positive direction because losses are weighted more than gains. While not entirely consistent with an assimilation-contrast view, prospect theory provides evidence that some deviations are weighted more heavily than others. The contrast aspect of the assimilation-contrast model argues that large differences, regardless of whether they are negative or positive, will be treated differently from small differences. Thus, an assimilation-contrast model suggests that setting expectations low or accurately would be preferred to setting them too high.
In a study of consumer satisfaction, Anderson (1973) found support for the assimilation-contrast model. Using an experimental design in which subjects were given different messages regarding a product, and then asked to evaluate various characteristics of the product, Anderson’s results showed that participants’ evaluations of the product varied directly with their expectations, until the magnitude of the difference was quite large. Once the difference became large, experiences varied inversely with expectations. Likewise, Coughlan and Connolly (2001) argued that satisfaction is a function of experiences evaluated in light of expectations. In two experiments, they asked individuals to predict their bowling scores and estimate a range within which the scores would fall. The results suggest that the surprise value of large differences caused those differences to have more of an impact than if one were to experience an outcome that is within an expected range of outcomes, thus supporting an assimilation-contrast model.

**Expectations Only and Experiences Only**

While not explicitly presented by Anderson (1973), two other models are of interest in understanding the relationship among expectations, evaluations, and some desired outcome: expectations only and experiences only. These models have been supported empirically in prior literature and provide an important benchmark against which more complex models can be compared. An expectations only view is consistent with the predictions of the technology acceptance model (TAM; Davis et al. 1989), in which users’ perceptions of the ease of use and usefulness of a system are obtained prior to its implementation. These a priori perceptions represent expectations about using the system. In an expectations only perspective, expectations directly predict outcomes, thus representing a perfect assimilation toward an individual’s a priori beliefs. In contrast, an experiences only model anchors outcomes on actual experiences and renders expectations inconsequential to the outcome evaluations.

Research has also supported both expectations only and experiences only models. For example, Pulakos and Schmitt (1983) found a positive relationship between expectations and satisfaction. However, Miceli (1986) argued that the impact of expectations may be a function of timing, meaning that an
expectations only model is more likely to hold when expectations are evaluated early in a process, such as shortly after an employee is hired when examining realistic job previews. Over time, the impact of expectations is hypothesized to diminish, ultimately resulting in an experiences only model. The experiences only model has been supported in research studying employee turnover and organizational commitment (Irving and Meyer 1994). Further, Hom et al. (1999) found support for an experiences only model in predicting a number of outcomes including organizational commitment, voluntary turnover, coping, and satisfaction. In contrast, in IS research, Davis and Venkatesh (2004) found that early perceptions (pre-implementation expectations) of a system were strong predictors of system use even months after implementation. Davis and Venkatesh (2004) also found that post-implementation measures were non-significant once pre-implementation measures were included in the model.

UNDERSTANDING COMPETING RESULTS

It is interesting to note that across and within domains of study, multiple expectations models have been supported. We propose that this is due to four key shortcomings associated with prior expectations research: (1) the reliance on a single model to explain the phenomenon; (2) the predominant use of linear models and analytical techniques; (3) the use of difference scores approach to analyses; and (4) the direct measurement of confirmation rather than the measurement of expectations and experiences separately.

In the majority of studies reviewed, a single model of expectation confirmation is employed. While employing a single theoretical perspective in a study is not uncommon, it does not allow for comparisons across models. Each of the models discussed above presents a different interplay between expectations and experiences in influencing outcomes. By testing individual models, the pattern of results emerges across studies, but a number of questions regarding subjects, settings, etc. render the results difficult to compare. In contrast, when multiple models are tested within the same data set, we can develop a clearer understanding of the conditions under which specific models will hold.
Even though the propositions predict non-linear 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 impacts of expectations and experiences on an outcome. 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 non-linear models could explain significant variance not explained by linear models (Edwards 2001). Thus, the use of linear modeling constrains our ability to discern the complex patterns theorized. In fact, in their post-hoc analysis, Staples et al. (2002) provide some evidence that non-linear relationships may exist between expectations, experiences, and outcomes.

Difference scores analysis has inherent methodological problems that have been highlighted in prior research (see Edwards 1995, 2002; Edwards and Harrison 1993; Edwards and Parry 1993; Edwards and Rothbard 1999). In essence, difference scores assume that expectations and experiences have equal and opposite impacts on the outcome. Difference scores have been shown to be less reliable than the component measures (Edwards 2002; Edwards and Cooper 1990) and conceal substantial differences in the effects of the components as the difference scores yield confounding results (Edwards 1994a). The outcomes using difference scores are a result of congruence between expected and experienced values rather than the components separately (Edwards and Harrison 1993). For example, in classic person environment (P-E) fit theory, French et al. (1982) used difference scores to determine the relationship between person, environment, and stress. Edwards and Harrison (1993) re-analyzed the data using polynomial regression analysis and not only found ambiguities in the results of P-E fit theory but also gave more in-depth understanding of the phenomenon. Of the 45 significant relations with strain reported by French et al. (1982), constraints imposed by difference scores were supported in only three cases.
Another measurement issue has been the use of direct measures of confirmation (e.g., Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Lee and Mowday 1987; Oliver 1977; Saks 1994; Suszko and Breaugh 1986) rather than measurement of expectations and experiences separately. Research taking this approach asks study participants to report the degree to which their expectations were met. Direct measurement is essentially used in research in order to circumvent the problems caused by difference scores (Irving and Meyer 1995). However, direct measurement is problematic because of the subsequent difficulty in understanding the relative impact of expectations and experiences on satisfaction (Irving and Meyer 1994, 1995). Further, Irving and Meyer (1994, 1995) reported that responses to met expectations questions appear to be disproportionately influenced by current experiences. While recalling the prior beliefs, individuals use the current beliefs as a benchmark because the current beliefs are more salient to them. Moreover, if individuals fail to recall their prior beliefs, they might guess and this guess is also based on present experiences as the present is more accessible to them (Ross 1989). This potential bias of the past beliefs with the present is consistent with the predictions of cognitive dissonance theory that suggests that as individuals attempt to limit their dissonance between expectations and experiences, they would underreport differences in order to remain cognitively consistent (Festinger 1962). Likewise, the hindsight bias suggests that individuals engage in revisionist history in order to create consistency (Christensen-Szalanski and William 1991; Hawkins and Hastie 1990). Thus, it is highly likely that when individuals with experience are asked to rate the degree to which their expectations were confirmed or disconfirmed, they will overstate the agreement between expectations and experiences. In this case, the pattern of results will appear similar to that of the assimilation model; however, due to the focus on expectation confirmation, it is difficult to determine if evaluations actually assimilated toward expectations or if expectations were revised post-hoc to be consistent with experiences.

To summarize, six models of expectation confirmation have been identified in the literature. Each of these models has empirical support within and across domains. A number of explanations exist to
explain these inconsistent results. In this study, we address the limitations in prior research by: (1) comparing all six models simultaneously; (2) collecting data on expectations and experiences at the appropriate times and independent of one another; and (3) using polynomial modeling to more accurately and comprehensively represent the roles of expectations and experiences in the models.

**POLYNOMIAL MODELING AND RESPONSE SURFACES AS SOLUTIONS**

Polynomial modeling presents an alternative technique for determining the separate and joint contribution of expectations and experiences to an outcome (see Edwards 2002). Edwards and Harrison (1993) proposed the use of polynomial regression to capture the nuances of the response surface associated with constructs traditionally assessed via difference scores and traditional linear regression models (see also Edwards and Parry 1993). An advantage of polynomial modeling is its ability to represent a wide variety of relationships, such as algebraic differences, absolute differences, and squared differences without the analytical limitations inherent in the methodological of prior expectation confirmation literature (Edwards 1994b). Therefore, to address the methodological shortcoming associated with the models of expectation confirmation, we assess expectations and experiences using separate measures and maintain this distinction throughout the analysis. This approach improves our ability to capture the impact of expectations and experiences separately and diminishes the impact of hindsight bias or dissonance reduction strategies. Polynomial models have been used to examine a variety of phenomena, such as goal congruence (e.g., Kristof-Brown and Stevens 2001), person-environment fit (e.g., Edwards and Harrison 1993), and self-other agreement (e.g., Atwater et al. 1998; Johnson and Ferstl 1999). Through the use of polynomial regressions, a more complete picture of the relationships among expectations, subsequent evaluations, and the outcome variable can be achieved, thus providing a deeper understanding of the phenomenon in question. In examining the relationship among expectations, experiences, and outcomes, the relationships for each model are translated into surface features. The resulting data are then tested to examine support for various models. Further, response surface analysis is a graphical technique that
allows a visual examination of component measures (e.g., expectations vs. experiences on a particular construct) against a dependent variable. The response surface analysis complements the information available through a polynomial regression analysis as the former provides a way to visualize the effects.

**METHOD**

In this section, we discuss the organizational setting, participants, data collection procedure, and measurement details.

**Organizational Setting, Participants, and Data Collection Procedure**

The setting for the study was a large-scale Intranet-based system for knowledge sharing within a large organization with nearly 8,000 employees. In addition to providing all information to employees from the human resource department, including benefits, forms, and social activities, the system could be used by employees to share information, both related to work and social activities. The organization’s objective with the system was to create a better push of information from the organization to the employees, provide a basic knowledge management system to facilitate sharing of knowledge, 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 (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 was a list of all employees in the organization, comprising about 8,000 employees. 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 2,800 employees. We contacted these employees by email to solicit their participation. One-thousand one-hundred and thirteen employees provided usable responses at both points of measurement, resulting in an overall response rate of almost 40%. Of the 1,113 responses, 383 were women (≈ 34%) and the average age was 35.8 years (SD = 9.92).
On average, respondents had just over six years of prior computer experience. The demographic profile of the respondents matched the profile of the sampling frame, thus alleviating concerns of non-response bias.

We administered two surveys that the participants returned within the first week. The first survey was administered after the completion of the organizationally-required training program on the new system ($t_1$). The second survey was administered after the users had substantial amount of time to use the system—i.e., six months ($t_2$). This approach is consistent with prior expectation disconfirmation, training, and individual technology acceptance research where individual reactions to the technology were studied (e.g., Bhattacherjee and Premkumar 2004; Davis et al. 1989; Venkatesh et al. 2003).

**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 Bhattacherjee and Premkumar 2004; Venkatesh et al. 2003). Various modified versions of these scales have been used extensively in prior research (e.g., Adams et al. 1992; Koufaris 2003; Lim and Benbasat 2000; 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. 2003). Seven-point Likert agreement scales were used in conjunction with the various 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.

**Polynomial Modeling**

Polynomial modeling involves examination of an outcome variable by regressing commensurate component measure along with the successive powers of these measures (Edwards and Harrison 1993; Edwards 2002). Commensurate measures are defined as the measures that express components in the same content dimension—e.g., received and desired pay, actual and desired autonomy (Edwards 2002).
Commensurate measurement is necessary to make a meaningful interpretation of the results in terms of congruence and for the conceptual relevance of the component measures (Edwards 1994a). Polynomial modeling uses hierarchical analysis of polynomial equations and may be applied either in a confirmatory or exploratory manner (Edwards 2001). The confirmatory approach involves identification of the regression equation corresponding to the theoretical model and relaxing the constraints applied by the theoretical model. 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 does not substantively differ from zero. For example, a squared difference score equation can be shown as:

\[ Z = b_0 + b_1 (X - Y)^2 + e \]  

The relaxed form of the above equation (equation 1) can be:

\[ Z = b_0 + b_1 X + b_2 Y + b_3 X^2 + b_4 XY + b_5 Y^2 + e \]  

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

**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 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 that is defined as a point at which slope of the surface is zero in all directions; (2) principal axes that 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 confirmation axis, 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.

Polynomial modeling requires a two-dimensional relationship to be represented in a three-dimensional space such that the distinction between expectations and experiences can be preserved (Edwards and Harrison 1993). Therefore, in order to perform the tests it was necessary to translate the six theoretical models into three-dimensional response surfaces, which we present next.

**ANALYTICAL REPRESENTATION OF THEORETICAL MODELS OF EXPECTATION CONFIRMATION**

As it is difficult to directly interpret equations associated with response surfaces, the slopes along lines of interest—here, the confirmation and the disconfirmation axes—provide a way to develop response surfaces that are consistent with the proposed theoretical relationships (Edwards and Parry 1993). Inherent in previous work using difference scores is the underlying assumption that the slope along the confirmation axis is equal to zero (Edwards and Parry 1993; Lambert et al. 2003). Polynomial modeling, however, enables examination of the slopes along both the confirmation and disconfirmation axes.

The state of congruence between expectations and experiences is associated with a high degree of outcome evaluations (Anderson 1973). However, evidence exists that the absolute level of promised and delivered inducements has a strong effect on these outcome evaluations. Lambert et al. (2003) examined the breach (a state similar to psychological dissonance) and fulfillment (a state similar to psychological consonance) of the psychological contract of employees in an organization. They found that a high level of fulfillment results in a higher satisfaction level than a low level of fulfillment. In the case of
information systems, prior research on technology acceptance indicates that high levels of both perceived ease of use and perceived usefulness are a preferential state when compared to low levels (Davis et al. 1989; Venkatesh and Davis 2000). While examining technology perceptions within the expectation confirmation framework, high levels of both expectations and experiences would result in a higher behavioral intention than low levels of expectations and experiences. It has also been observed that desired outcomes are lowest in the low-expectation and low-experience scenario and highest in the high-expectation and high-experience scenario (Olshavsky and Miller 1972). Therefore, the level of satisfaction among all the models would be lower for confirmation achieved at lower levels of expectations and experiences compared to expectation confirmation achieved at higher levels. This is equivalent to stating that the response surface is expected to have a positive and linear slope along the confirmation axis.

The disconfirmation axis is of particular interest because the slope of the line along this axis corresponds directly with the slope of the line generated through analysis of expectation confirmation models with difference scores. For example, the slope along the disconfirmation axis for a response surface representing the assimilation model would be identical to the slope of the 2-dimensional assimilation model predicted by prior research. Therefore, in generating the response surfaces, a positive linear slope along the confirmation axis and the theoretically appropriate slope along the disconfirmation axis were used as solution constraints. Next, we discuss the analytical representation of each of the six theoretical models of expectation confirmation.

**Assimilation Model**

Based on cognitive dissonance theory, a psychological state of consonance exists when there is no deviation from one’s expectations, while a psychological state of dissonance exists when there is a significant deviation from one’s expectations (Festinger 1962). These states of consonance and dissonance are represented on a three-dimensional plot by the confirmation and disconfirmation axes respectively. The left hand corner of the plot represents a point with maximum expectation and minimum
experience levels, while the right hand corner of the plot represents a point of minimum expectation and maximum experience levels. A three-dimensional depiction of the assimilation model is shown in Figure 1(a) and is represented by the equation:

\[ Z = b_0 + b_1X + b_2Y + e \]  

(3)

Where, \( Z = \text{Behavioral intention} \); \( X = \text{Experience} \); \( Y = \text{Expectation} \)

As the assimilation model suggests that a higher level of expectation is associated with more favorable outcomes, the level of the outcome variable is biased towards the level of expectation (Szajna and Scamell 1993). Therefore, the value of behavioral intention along the disconfirmation axis would be higher on the left hand corner (region where expectations are highest) of the plot and lower on the right hand corner of the plot (region where expectations are lowest). Further, the slope of the disconfirmation axis—\( a_y \)—would be negative, though the absolute value of \( a_y \) would be less than the slope of the confirmation axis—\( a_x \). Per the assimilation model, expectations have a stronger influence than experiences on behavioral intention. Therefore, the expectation coefficient (\( b_2 \)) must necessarily be greater than the experience coefficient (\( b_1 \)) for response surfaces supporting this theoretical model. These tests for assimilation model can be summarized as:

**Test 1.** \( b_1 > 0 \) and \( b_2 > 0 \); **Test 2.** \( b_2 > b_1 \); **Test 3.** \( a_x > 0 \) and \( a_y < 0 \); and **Test 4.** \( |a_x| > |a_y| \).

**Contrast Model**

The contrast model suggests that unmatched expectations create a surprise effect or contrast between one’s expectations and experience (Anderson 1973) and the ultimate outcome evaluations are based on the direction and size of the gap between expectations and experiences (Sherif and Hovland 1961). Therefore, behavioral intention increases as experiences exceed expectations and decreases as experiences falls short of expectations. A three-dimensional depiction of the contrast model is shown in Figure 1(b) and is represented by the equation:

\[ Z = b_0 + b_1X + b_2Y + e \]  

(4)
Where, \( Z = \) Behavioral intention; \( X = \) Experience; \( Y = \) Expectation

A response surface representing these theoretical relationships would have a very high value of behavioral intention along the disconfirmation axis at points where experiences are very high and expectations are very low. As experiences decrease and expectations increase along the disconfirmation axis, the value of behavioral intention will decrease. Therefore, the slope of the disconfirmation axis—i.e., \( a_y \)—would be positive. However, the slope of the disconfirmation axis would be higher than the slope of the confirmation axis (\(|a_y| > |a_x|\)) because positive disconfirmation is associated with a higher level of outcome (e.g., behavioral intention). Experiences have a higher impact on behavioral intention than expectations. Therefore, the coefficient of \( X \) (\( b_1 \)) should be higher than the coefficient of \( Y \) (\( b_2 \)). As the size of the gap between expectations and experiences determines behavioral intention, high maximum and minimum values of the gap can be achieved by having an opposite sign on the coefficients of \( X \) and \( Y \). Therefore, we expect the coefficients of \( X \)—i.e., \( b_1 \)—to be positive and \( Y \)—i.e., \( b_2 \)—to be negative. These tests for the contrast model can be summarized as:

**Test 1.** \( b_1 > 0 \) and \( b_2 < 0 \); **Test 2.** \( b_2 = -b_1 \); **Test 3.** \( a_x > 0 \) and \( a_y > 0 \); and **Test 4.** \( |a_x| < |a_y| \).

**Generalized Negativity Model**

The generalized negativity model suggests that if a person expects a certain event but experiences a different event, a psychological state of dissonance occurs (Aronson and Carlsmith 1962; Carlsmith and Aronson 1963). This model further suggests that when one’s experience falls short of expectations, a negative disconfirmation results in lower behavioral intention and when one’s expectations are less than the experiences, a positive disconfirmation results in lower behavioral intention (Anderson 1973). A three-dimensional depiction of the generalized negativity model is shown in figure 1(c) and can be represented by the following equation:

\[
Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e
\]  

(5)

Where, \( Z = \) Behavioral intention; \( X = \) Experience; \( Y = \) Expectation
A response surface representing these theoretical relationships would take on a positive slope when expectations are greater than experiences and a negative slope when experiences fall short of expectations because the level of outcome (e.g. behavioral intention) increases with the decrease in the degree of disconfirmation. The change in slope from positive to negative would require us to represent the surface with a quadratic function with a change in slope occurring at the confirmation axis. As the positive and negative disconfirmation of expectations have equal and opposite effects on behavioral intention, we expect the linear slope of the disconfirmation axis to be equal to zero \((a_y = 0)\) and coefficients of \(X\) and \(Y\) to have approximately the same magnitude \((b_1 = b_2)\). Moreover, the change in slope from positive to negative would require the quadratic slope along the disconfirmation axis to be significant and negative \((a_{y^2} < 0)\).

These tests can be summarized as:

**Test 1.** \(b_1 = b_2;\)**  
**Test 2.** \(a_y = 0;\)**  
**Test 3.** \(a_{y^2} < 0;\) and  
**Test 4.** \(a_{x^2} = 0.\)

**Assimilation-contrast Model**

The assimilation-contrast model takes on properties of both the assimilation and contrast models, thus resulting in a more complex response surface. When the differences between expectations and experiences are small, behavioral intention is determined largely by expectations, consistent with the assimilation model. On the contrary, when differences between expectations and experiences are large, behavioral intention is determined by the level of gap between expectations and experiences, consistent with the contrast model (Anderson 1973). A three-dimensional depiction of the assimilation-contrast model is shown in figure 1(d) and can be represented by the following equation:

\[
Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6X^3 + b_7X^2Y + b_8XY^2 + b_9Y^3 + e \tag{6}
\]

Where, \(Z = \) Behavioral intention; \(X = \) Experience; \(Y = \) Expectation

Similar to the other models, the differences between the experience and expectations are represented by the disconfirmation axis in a three-dimensional plot. The differences between experiences and expectations decrease as we move along the disconfirmation axis from the corner of the plot towards
the confirmation axis. Therefore, the response surface represented by the assimilation-contrast model is wave-shaped along the disconfirmation axis. As the wave shaped graph along the disconfirmation axis has two inflection points, it requires that the cubic form of the response surface equation be significant. The cubic function along the disconfirmation axis would require cubic slope—i.e. $a_y^3$—to be significant and high and the quadratic slope —i.e. $a_y^2$—to be zero. Consistent with the theoretical relationship of expectation-disconfirmation theory and other theoretical models, the slope along the confirmation axis should be linear and positive. Therefore, the quadratic—i.e. $a_x^2$—and the cubic—i.e. $a_x^3$—slope along the confirmation axis should be zero. These tests can be summarized as:

**Test 1.** $a_y^3 \neq 0$; **Test 2.** $a_y^2 = 0$; **Test 3.** $a_x^2 = 0$; and **Test 4.** $a_x^3 = 0$.

**Expectations Only and Experiences Only**

The expectations only model suggests that behavioral intention is determined entirely by expectations, with only the Y coefficient—i.e. $b_2$—expected to be positive and significant. Similarly, the experiences only model suggests that behavioral intention is determined entirely by experiences, with only the X coefficient —i.e. $b_1$—expected to be positive and significant. However, the absolute value of the slope for the confirmation and disconfirmation axes should be equal ($|a_x| = |a_y|$) for both expectations only and experiences only models indicating that there is no interaction between expectations and experiences in either model.

Table 1 lists a summary of the expected pattern of coefficients with constraints for each of the six models and Table 2 shows the summary of expected slopes along the lines of interest.
Table 1: Expected Pattern of Coefficients with Constraints

<table>
<thead>
<tr>
<th>Model</th>
<th>Monotonic</th>
<th>Quadratic</th>
<th>Cubic</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assimilation</td>
<td>+</td>
<td>+</td>
<td></td>
<td>b₁ &gt; 0; b₂ &gt; 0; b₂ &gt; b₁;</td>
</tr>
<tr>
<td>Contrast</td>
<td>+</td>
<td>-</td>
<td></td>
<td>b₁ &gt; 0; b₂ &lt; 0; b₂ = - b₁; aₓ &gt; 0; aᵧ &gt; 0;</td>
</tr>
<tr>
<td>Generalized Negativity</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>b₁ = b₂; aₓ = 0; aᵧ² &lt; 0; aᵧ² = 0</td>
</tr>
<tr>
<td>Assimilation-contrast</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>aₓ³ ≠ 0; aᵧ² = 0; aₓ² = 0; aᵧ³ = 0</td>
</tr>
<tr>
<td>Expectation</td>
<td>+</td>
<td>0</td>
<td></td>
<td>b₁ = 0; b₂ &gt; 0;</td>
</tr>
<tr>
<td>Experience</td>
<td>0</td>
<td>+</td>
<td></td>
<td>b₁ &gt; 0; b₂ = 0;</td>
</tr>
</tbody>
</table>

Note: X = experience; Y = expectation; aₓ = linear slope along confirmation axis; aᵧ = linear slope along disconfirmation axis; aₓ² = quadratic slope along confirmation axis; aᵧ² = quadratic slope along disconfirmation axis; aₓ³ = cubic slope along confirmation axis; and aᵧ³ = cubic slope along disconfirmation axis.

Table 2: Slopes Along Lines of Interest

<table>
<thead>
<tr>
<th>Model</th>
<th>Confirmation Axis X = Y</th>
<th>Disconfirmation Axis X = -Y</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>aₓ</td>
<td>aₓ²</td>
</tr>
<tr>
<td>Assimilation</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Contrast</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Generalized Negativity</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>Assimilation-contrast</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>Experience Only</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Expectation Only</td>
<td>+</td>
<td></td>
</tr>
</tbody>
</table>

Note: aₓ = linear slope along confirmation axis; aᵧ = linear slope along disconfirmation axis; aₓ² = quadratic slope along confirmation axis; aᵧ² = quadratic slope along disconfirmation axis; aₓ³ = cubic slope along confirmation axis; aᵧ³ = cubic slope along disconfirmation axis.
Figure 1: Three-dimensional Plots of the Expectation Confirmation Models

Figure 1(a): Assimilation Model

Figure 1(b): Contrast Model

Figure 1(c): General Negativity Model

Figure 1(d): Assimilation–contrast Model

Figure 1(e): Experience–only Model

Figure 1(f): Expectation–only Model
ANALYSIS

To ensure the conceptual relevance of the component measures to one another and to meaningfully interpret the results, we used commensurate measurement (see Edwards 2002). Commensurate measurement means that the respondents express the components in the same content dimensions. Examples of commensurate measurement include: promised and delivered skill development; promised and delivered recognition; and actual and desired autonomy (Edwards 1994b; Lambert et al. 2003). Therefore, only one set of constructs (e.g., expected perceived usefulness and experienced perceived usefulness) are examined as predictors in a single model to predict behavioral intention so as to meaningfully interpret them graphically. A number of studies in the management, organization behavior, and personnel psychology literature have developed a series of models with different sets of predictors to examine the same dependent variable—for example, Edwards and Rothbard (1999) examined autonomy supplies, autonomy values, and their associated higher-order terms as predictors of family well-being; they also examined relationship supplies, relationship values, and their associated higher-order terms as predictors of family well-being (see also Edwards 1994a, 1994b, 2002; Lambert et al. 2003).

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 minimum criteria set by 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 and perceived ease of use. Scale-centering is done by subtracting the midpoint of the scales from the actual score. Scale-centering reduces multicollinearity problems and also allows meaningful interpretation of the coefficients of the polynomial equations (Edwards 2002). Scores produced after scale-centering ranged from -3 to +3. 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 if: (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 if a meaningful relationship among the variables of the interest exists even after first factor was controlled. Because this condition was also satisfied, we concluded that our sample does not suffer from problems associated with the common method bias.

We used a jackknife procedure to estimate the significance level of the various components of response surfaces. Non-parametric procedures, such as jackknifing and bootstrapping, are used when traditional techniques, such as regression analysis, do not provide formulas for the estimation of specific expressions—here standard errors and significance levels for response surface components, such as the slopes of confirmation and disconfirmation axes (Efron and Gong 1983). The jackknifing procedure begins with dropping one observation from the sample and calculating the expression of interest (e.g., slope of confirmation axis). The excluded observation is then replaced with another observation and the expression of interest is calculated again. This procedure continues until all the observations in the sample are dropped exactly once. Finally, assessing the variation in the estimated values of expression of interest allows us to determine the standard errors for that expression. These are then used to determine the significance level for the expression.

RESULTS

For all analyses, measure of X represents the experienced usefulness or ease of use, Y represents the expected amount of usefulness or ease of use, and Z represents behavioral intention. All measurement scales showed high reliability, with the Cronbach alpha coefficients exceeding 0.8 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. All the constructs were correlated, with the highest correlation among independent variable pairs being between expected usefulness and experienced usefulness. Also, experienced usefulness had the highest
correlation with the dependent variable of behavioral intention to continue using the system. Table 3 shows the reliabilities, descriptive statistics, and the correlations for all the 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 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 (e.g., Davis 1989; Mathieson 1991; Taylor and Todd 1995; Venkatesh and Davis 2000).

Table 3. Descriptive Statistics and Correlations

<table>
<thead>
<tr>
<th></th>
<th>Cronbach’s Alpha</th>
<th>Mean</th>
<th>SD</th>
<th>Expected PU</th>
<th>Expected PEOU</th>
<th>Experienced PU</th>
<th>Experienced PEOU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected PU</td>
<td>0.94</td>
<td>3.91</td>
<td>1.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected PEOU</td>
<td>0.93</td>
<td>3.77</td>
<td>1.07</td>
<td>0.28***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experienced PU</td>
<td>0.90</td>
<td>4.30</td>
<td>1.14</td>
<td>0.51***</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experienced PEOU</td>
<td>0.95</td>
<td>4.47</td>
<td>1.33</td>
<td>0.14*</td>
<td>0.13*</td>
<td>0.23***</td>
<td></td>
</tr>
<tr>
<td>BI</td>
<td>0.88</td>
<td>4.20</td>
<td>1.28</td>
<td>0.41***</td>
<td>0.07</td>
<td>0.49***</td>
<td>0.17*</td>
</tr>
</tbody>
</table>

Notes:
PU: Perceived Usefulness; PEOU: Perceived Ease of Use; BI: Behavior intention to continue using the system.
*p<.05; ** p<.01; *** p<.001.

Confirmatory Analysis

For conducting confirmatory tests for the six models, we examined the unconstrained polynomial models (here, linear and quadratic) for perceived usefulness (see Table 4) and perceived ease of use (see Table 5). The unconstrained equations for both perceived usefulness and perceived ease of use yielded significant values for $R^2$ and the coefficients of $X$ and $Y$ for the first-order equations and subsequent higher-order equations. The coefficients of the regression equations and the slopes along the lines of interest were used to examine the constraints imposed by various theoretical models that we discuss next.
Table 4. Unconstrained Model: Predicting Behavioral Intention Using Usefulness

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Independent Variables</th>
<th>First-order Linear Equation</th>
<th>Second-order Quadratic Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>B</td>
<td>SE</td>
<td>β</td>
</tr>
<tr>
<td>Behavioral</td>
<td>X 0.40</td>
<td>1.00</td>
<td>0.08</td>
</tr>
<tr>
<td>Intention</td>
<td>Y 0.44</td>
<td>0.44</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>X²</td>
<td>-0.60</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>XY</td>
<td>1.41</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>Y²</td>
<td>-0.40</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Notes:
X: Experienced perceived usefulness; Y: Expected perceived usefulness.
* p<.05; ** p<.01; *** p<.001.

Table 5. Unconstrained Model: Predicting Behavioral Intention Using Perceived Ease of Use

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Independent Variables</th>
<th>First Order Linear Equation</th>
<th>Second Order Quadratic Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>B</td>
<td>SE</td>
<td>β</td>
</tr>
<tr>
<td>Behavioral</td>
<td>X 0.16</td>
<td>0.32</td>
<td>0.03</td>
</tr>
<tr>
<td>Intention</td>
<td>Y 0.04</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>X²</td>
<td>-0.06</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>XY</td>
<td>0.10</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>Y²</td>
<td>-0.10</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Notes:
X: Experienced perceived ease of use; Y: Expected perceived ease of use.
* p<.05; ** p<.01; *** p<.001.

Most of the constraints imposed by assimilation model for perceived usefulness predicting behavioral intention were satisfied as: (1) the coefficients on both X and Y were positive (test 1); (2) the slope along confirmation axis (aₓ = 1.44) was positive and the slope along the disconfirmation axis was negative (aᵧ = -0.56; test 3); and (3) the absolute value of the slope along the confirmation axis was higher than the absolute value of the slope along the disconfirmation axis (test 4). However, this model was not supported for perceived usefulness because: (1) the coefficient for Y was not greater than the coefficient of X (test 2); and (2) the results of an F-test showed that the variance explained by higher order (quadratic)
terms (R² = 0.63) was substantially higher than the variance explained by first order terms (R² = 0.40).

Similarly, for perceived ease of use predicting behavioral intention, constraints imposed by the assimilation model were not supported because the coefficient of Y was not greater than the coefficient of X (test 2).

Also, based on the results of an F-test, higher variance was explained by higher-order (quadratic) terms (R² = 0.23) than the linear terms (R² = 0.16). This provided further evidence of rejection of the assimilation model for perceived ease of use predicting behavioral intention.

The constraints imposed by the contrast model were not satisfied by either perceived usefulness or perceived ease of use models as: (1) the coefficient of Y was positive for both perceived usefulness and perceived ease of use (test 1); (2) the coefficient of Y was not equal and opposite to the coefficient of X (test 2); (3) the linear slope along the disconfirmation axis was negative (test 3); and (4) the absolute value of the slope along the confirmation axis was higher than that of the disconfirmation axis (test 4). Moreover, variance explained by higher order (quadratic) terms was substantially higher than the variance explained by first order terms. Therefore, we found no support for the contrast model.

The three-dimensional representation of the generalized negativity model required a second-order polynomial equation. In the case of perceived usefulness, because the value of b₁ (b₁ = 0.22) was equal to b₂ (b₂ = 0.24), the first constraint was satisfied (test 1). The value of the linear slope along the disconfirmation axis (a₁ = 0.02; p < .01) was not significantly different from zero (test 2) and the non-linear slope (a₂ = -2.41; p < .01) was significant and negative (test 3). However, a small non-zero value of the curvilinear slope along the confirmation axis (a₃ = 0.41; p < .01) indicated that test 4 was not fully satisfied.

Therefore, the generalized negativity model was only partially supported. For perceived ease of use, because the value of b₁ (0.20) was not equal to b₂ (0.03), test 1 was not satisfied. Along the disconfirmation axis, the value of the linear slope (a₁ = 0.17; p < .01) was very close to zero and the curvilinear slope (a₂ = -0.26; p < .01) was negative. This indicates that tests 2 and 3 were satisfied. Further, a significant but small value of the curvilinear slope along the confirmation axis (a₃ = -0.06; p <
.01) indicated that test 4 was also satisfied indicating that the generalized negativity model was partially supported for perceived ease of use predicting behavioral intention.

The assimilation contrast model required a cubic equation. For perceived usefulness, it was observed most of the constraints imposed by the theoretical model were not satisfied as: (1) the cubic slope along the disconfirmation axis \( a_y^3 = 0.59; p < .01 \) though significant was fairly small (test 1); the quadratic slope along the disconfirmation axis \( a_y^2 = -1.70; p < .01 \) was not equal to zero (test 2); and (3) the quadratic \( a_x^2 = 0.30; p < .01 \) and cubic \( a_x^3 = 1.41; p < .01 \) slopes along the confirmation axis were not equal to zero (tests 3 and 4). This indicated that the assimilation contrast model was not supported for perceived usefulness. For perceived ease of use, the quadratic slope along the disconfirmation axis \( a_y^2 = -0.24; p < .01 \) and the quadratic \( a_x^2 = -0.04; p < .01 \) and cubic \( a_y^2 = -0.02; p < .01 \) slope along confirmation axis were very low (tests 2, 3, and 4). However, the cubic slope along the disconfirmation axis \( a_y^3 = -0.10; p < .01 \) was also fairly small. Therefore, the assimilation-contrast model was not supported for ease of use.

Support for experiences only and expectations only models required the coefficient of either X or Y to be zero. Because the coefficients of both X and Y were non-zero for both perceived usefulness and ease of use predicting behavioral intention, thus not supporting either of the two models.

Results of the confirmatory analysis showed that out of the six existing models, the generalized negativity model is the best existing model, however it was not completely supported for either ease of use or usefulness. We conducted exploratory analysis using the second-order quadratic equation to propose a new model that builds upon and goes beyond the existing generalized negativity model.

**Exploratory Analysis**

The response surface depicted by perceived usefulness predicting behavioral intention was concave as shown in Figure 2. The stationary point (the point at which the slope of the surface is zero in all directions) for the surface was close to the origin \( X_o = -0.49, p < .01; Y_o = -0.59, p < .01 \). The first
principal axis (line along which the slope of a concave surface is minimum) passed through the origin (equation of first principal axis was $Y = -0.02 + 1.15 X$). The slope of the first principal axis was not significantly different from 1 ($p < .001$), suggesting that there was no significant rotation of the surface along the confirmation axis. Moreover, the lateral shift of the surface along the disconfirmation axis was negligible (equation for the second principal axis is $Y = -1.01 - 0.87 X$). 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. Moreover, 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. The positive quadratic slope along the confirmation axis indicated that the surface was somewhat convex along the confirmation axis. Similarly, the slope of the surface along the disconfirmation axis ($U_1=-U_2$) showed non-significant linear ($a_x=0.02$) and significant quadratic ($a_x^2=-2.40$, $p < .01$) components. The strong negative quadratic slope indicated that the surface along the disconfirmation axis was strongly concave. In combination, these results indicated three key effects. First, behavioral intention decreased as experienced usefulness deviated from the expected usefulness in either direction. Second, as the surface had an overall positive slope along the confirmation axis, behavioral intention was higher when expected and experienced usefulness were both high than when both were low. Third, the slight convex nature of the surface along the confirmation axis indicated that behavioral intention was lowest along the confirmation axis when both expected and experienced usefulness were moderate (at the center) and increased in both directions.

The surface depicted by perceived ease of use predicting behavioral intention, as shown in, Figure 3, was also concave. The stationary point of the surface was close to the right edge of the X, Y plane ($X_o = 3.07$, $p < .01$; $Y_o = 1.69$, $p < .01$). The first principal axis almost passed through the origin (equation of first principal axis was $Y = -0.39 + 1.69 X$). Because the slope of the first principal axis was not significantly different from 1 ($p < .01$) and the intercept was very close to 0 ($p < .01$), there was no significant rotation or
lateral shift in of the surface along the disconfirmation line. Therefore, the maximum value of behavioral intention was along the confirmation axis. Also, the slope of this surface along the confirmation axis was positive and showed linear ($a_x=0.23$, $p < .01$) and quadratic ($a_x^2=-0.06$, $p < .01$) components. The slope of the surface along the disconfirmation axis ($U_1=-U_2$) showed significant linear ($a_x=0.17$, $p < .01$) and quadratic ($a_x^2=-0.26$, $p < .01$) components. The negative quadratic slope indicated that the surface along the disconfirmation axis was concave. In combination, these results indicated three key effects. First, behavioral intention decreased as experienced perceived ease of use deviated from the expected perceived ease of use in either direction. Second, because the surface had an overall positive slope along the confirmation axis, behavioral intention was higher when the absolute value of both expected and experienced perceived ease of use was higher than when both were low. Third, the positive slope of the disconfirmation axis indicated that the negative influence on behavioral intention was stronger for negative disconfirmation as compared to positive disconfirmation indicating that losses loom larger than gains.

Figure 2: Response Surface for Perceived Usefulness Predicting Behavioral Intention
DISCUSSION

This study compared six different theoretical models that outlined possible complex interactions between expectations and experiences in determining a key outcome—here, behavioral intention to continue using a system. In addition, expectations only and experiences only models were compared. The results of this study offer three contributions to research. First, we discussed the primary models used in expectation research and presented the corresponding analytical representations. Second, we conducted an empirical comparison of the different models while remedying critical methodological and analytical shortcomings in prior expectation confirmation research. Finally, we demonstrated that a complex relationship exists between expectations and experiences. The results from the current work examining aggregate expectations and experiences as predictors demonstrates that, of the existing models of expectation confirmation, the generalized negativity model comes closest to approximating the impact of expectations and experiences on behavioral intention.
A key finding is that the impact of expectations and experiences on intention differs for ease of use and usefulness, and both models differ somewhat from the generalized negativity model. Figure 1 shows that the response surface for usefulness follows the generalized negativity model reasonably well. There is, however, one interesting difference at the midpoint. When expectations and experiences are both equal to zero (i.e., at the midpoint), intention is actually lower than in the other instances when expectations and experiences are equal, which leads to the highest intention. It is possible that past experience with information systems implementation has an impact on the usefulness expectations and experiences. If prior systems were marketed to employees in such a way as to keep expectations about the middle of the road, prior experiences with those systems may be influencing current evaluations. An important area for future research is to incorporate prior implementation experiences in models of expectation confirmation.

A somewhat different picture emerges for ease of use in Figure 2. While ease of use also somewhat follows the generalized negativity model, it is important to note that when experiences are lower than expectations, the negative outcome is stronger than when experiences exceed expectations. This deviation from the generalized negativity model is consistent with a contrast model (e.g., Kopalle and Lehman 1999) in which the size and direction of the difference between experiences and expectations has an impact on ultimate outcome evaluations. In addition, this result is consistent with prospect theory (Kahneman and Tversky 1979) that suggests that losses have more of an impact than gains. This result is not entirely surprising, given the general expectation that graphical user interfaces lead to easier to use systems. Thus, when a system is not as easy to use as expected, intentions to use the system are reduced. Our results demonstrated that for ease of use, a hybrid model integrating generalized negativity and contrast (for losses) is most appropriate for explaining intention.

When comparing the models for usefulness and ease of use, it is interesting to note that there are differences. Prior technology acceptance research has demonstrated that ease of use and usefulness behave in different ways when considered together as predictors of behavioral intention. For instance,
ease of use is frequently considered a hurdle that plays a more significant role in the early stages of experience with a system whereas usefulness is a stable and continued determinant (see Venkatesh et al. 2003 for a review). In the current study, usefulness more closely approximates the generalized negativity model deviating at the midpoint, while ease of use deviates from it when expectations are not met. These deviations may be attributable to the nature of ease of use and usefulness. Specifically, usefulness requires a context—a specific system is useful or not useful with respect to a person’s job context (see Venkatesh and Davis 2000). Ease of use, on the other hand, is a function of largely of individual characteristics even after substantial experience with the system (see Venkatesh 2000). Thus, the underlying mechanisms by which usefulness and ease of use form and change differ fundamentally and this could be contributing to the different results observed in the case of each of those constructs.

Not only is this work one of the first studies to test the competing theoretical explanations related to expectation confirmation in a single study, but also it is one of the first studies to minimize potential methodological and analytical flaws. Clearly, the results provide support for the complexity of the interaction between experiences and expectations in predicting a key outcome—here, behavioral intention to continue using a system. 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. In addition, by measuring expectations and experiences separately, we determined the relative impact of each of the variables—rather than assuming they have equal and opposite impacts (as with difference scores)—and we are able to reduce the potential for hindsight bias that occurs when disconfirmation is measured directly. In this way, we address the methodological gaps of prior research and urge future researchers to follow suit.

The results of this research provide another data point demonstrating the power of polynomial modeling for understanding organizational phenomena. These results provide evidence that studying information systems 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 avoid the use of linear and difference scores models when examining issues of fit or congruence. In general, polynomial modeling will identify a linear relationship only when truly exists.

While a number of studies have demonstrated the appropriateness of polynomial models in a variety of contexts (e.g., Antonioni and Park 2001; Edwards 1994a, 1994b; 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. 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 1990), 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.

There are many important future research directions worth considering that will help identify critical contingencies. Identifying appropriate contingencies is critical before drawing conclusions regarding the superiority of one model or another. In our study, individual differences were not explicitly modeled. It is possible that different types of individuals—i.e., different personality profiles—could react very differently and better fit one type of model or another. For example, it is possible that more conscientious individuals may respond in ways consistent with a particular model, while less conscientious individuals may respond in ways consistent with a different model. Alternatively, those who are high vs. low on performance goal orientation or learning goal orientation could fit different models. In addition, some individuals set their own expectations low in order to avoid being disappointed, while others are more optimistic and expect the best. Similarly, in our study, employees’ specific levels of fit with their job or organization were not modeled.
Once again, it is possible that certain models will match certain levels of fit. Thus, this work suggests important directions for future work that will integrate these findings with important streams of research in organizational behavior while simultaneously furthering our understanding of expectation confirmation.

From a practical perspective, the results of this research suggest that the impact of expectations is as significant as anticipated. The key thing to note is the importance of organizations setting accurate expectations. The generalized negativity model indicates that for any deviation from expectations, a negative outcome will result. Thus, the common wisdom of setting low expectations in hopes of exceeding them could prove just as detrimental to organizations as setting high expectations that are not met. Further, our results demonstrated that there is an increased negative impact when expectations of ease of use are not met. Thus, realistic previews of the system, with respect to its ease of use and usefulness are essential to successful implementation of information systems.

CONCLUSIONS

This research examined the relationship among expectations, experiences, and the outcome of behavioral intention to continue using a system. Specifically, using polynomial modeling, we tested the six theoretical models of expectation confirmation. The results did not fully support any of the existing models in the case of usefulness or ease of use as predictor. Rather a modified generalized negativity model for both ease of use and usefulness was suggested. This work provides key insights into the role of expectations and experiences in intention formation, with a polynomial model being supported.

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