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EXPECTATION CONFIRMATION IN INFORMATION SYSTEMS RESEARCH: A TEST OF SIX COMPETING MODELS

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EXPECTATION CONFIRMATION IN IS RESEARCH: A TEST OF SIX COMPETING MODELS

ABSTRACT

Expectation confirmation research in general, and in information systems (IS) in particular, has produced conflicting results. In this paper, we discuss six different models of expectation confirmation: assimilation, contrast, generalized negativity, assimilation-contrast, experiences only, and expectations only. Relying on key constructs from the technology acceptance model (TAM), we test each of these six models that suggests different roles for expectations and experiences of the key predictor—here, perceived usefulness—and their impacts on key outcomes—here, behavioral intention, use, and satisfaction. Data were collected in a field study from 1,113 participants at two points in time. Using polynomial modeling and response surface analysis, we provide the analytical representations for each of the six models and empirically test them to demonstrate that the assimilation-contrast is the best existing model in terms of its ability to explain the relationships between expectations and experiences of perceived usefulness and important dependent variables—namely, behavioral intention, use, and satisfaction–in individual-level research on IS implementations.

KEYWORDS: Expectations, disconfirmation, software use, polynomial modeling, response surface analysis

INTRODUCTION

Understanding the relationship between a priori expectations and a posteriori evaluations is an important issue for researchers and practitioners in a variety of domains—e.g., information systems (IS; e.g., Bhattacherjee and Premkumar 2004; Ginzberg 1981; Heng et al. 2003; Szajna and Scamell 1993; Tan et al. 1999), work environment (e.g., Edwards and Rothbard 1999; Greenhaus et al. 1983; Kristof-Brown and Guay 2010), and consumer purchases (e.g., Cadotte et al. 1987; Kopalle and Lehmann 2001). Prior work in organizational behavior, psychology, and marketing has developed and empirically tested at least six different models of expectation disconfirmation—namely, assimilation, contrast, generalized negativity, assimilation-contrast, expectations only, and experiences only (e.g., Anderson 1973; Churchill and Suprenant 1982; Festinger 1962; Hom et al. 1999; Irving and Meyer 1994; Klein 1999; Oliver 1977, 1980; Yi 1990). Each of these different models has been supported to some extent in empirical research, albeit in different domains. Support for the assimilation model can be found in the service quality literature (e.g., Boulding et al. 1993), support for the contrast model can be found in the realistic job preview literature (e.g., Dugoni and Ilgen 1981; Wanous 1992), support for the generalized negativity model can be found in the social psychology literature (e.g., Carlsmith and Aronson 1963), and support for the assimilation-contrast model can be found in the marketing literature (e.g., Anderson 1973; Coughlan and Connolly 2001). Finally, the simpler expectations only and experiences only models have been supported in the personnel psychology literature (e.g., Pulakos and Schmitt 1983; Irving and Meyer 1994). Consequently, there is some confusion regarding the relationships among expectations, experiences, and outcomes. It is worth noting that expectation confirmation models are examined in specific contexts. It is thus possible that the observed differences may be attributed to the context of the study. Such differences based on the context are important to understand and constitute a key frontier for theory development and knowledge creation (see Johns 2006).

The context of interest in this work is IS implementation. This prompts us to turn to the IS literature that has had a long history of research on expectations, including some of the recent work of the authors of this paper (e.g., Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Brown et al. 2012; Brown et al. 2008; Ginzberg 1981; Staples et al. 2002; Szajna and Scamell 1993; Tan et al. 2003; Tan et al. 1999; Thatcher et al. 2011; Venkatesh and Goyal 2010). Some of the general models of expectation confirmation have been used and supported in different IS studies—e.g., assimilation model (Lankton and McKnight 2012; Szajna and Scamell 1993), contrast model (Staples et al. 2002), generalized negativity model (e.g., Ginzberg 1981; Tan et al. 1999; Venkatesh and Goyal 2010), modified assimilation-contrast model (Brown et al. 2012), expectations only model (Davis and Venkatesh 2004) and modified experiences only model (Brown et al. 2008). We elaborate on this literature next, with an emphasis on some of our recent work on this topic, so we can best explain how the current paper builds both on prior work on this topic in general and on our prior work in particular.

Drawing on the methodological and analytical advances in the organizational behavior literature (e.g., Edwards 2002), Venkatesh and Goyal (2010) identified gaps in the expectation confirmation research in IS. Venkatesh and Goyal contend that expectation confirmation research in IS has primarily focused on linear relationships and the direct measurement of disconfirmation. Linear relationships fail to reveal the complexities in theories of congruence whereas the direct measurement of disconfirmation distorts the joint influence of expectations and experiences on various outcomes (see Edwards 2002; Irving and Meyer 1995). Using polynomial modeling and response surface methodology, Venkatesh and Goyal argued that disconfirmation in general was bad and behavioral intention to use a system was highest when user expectations of a system were confirmed. Much prior polynomial modeling in IS (e.g., Oh and Pinsonneault 2007; Venkatesh and Goyal 2010) and reference disciplines (e.g., Brown et al. 2008; Edwards and Cable 2009) was conducted using only second-order (quadratic) equations. Brown et al. (2012) developed the analytical representations for third-order (cubic) equations and presented a more comprehensive model of expectation confirmation in IS. In this model, Brown et al. demonstrated that it is important to account for both the magnitude and the direction of the difference between experiences and expectations. Further, Brown et al. found that a cubic model was the best to explain the nuances of complex relationships among perceived usefulness expectations, experiences, and actual technology use because a cubic model was necessary to adequately represent the influence of both the magnitude and the direction of confirmation/disconfirmation of perceived usefulness on technology use.

The current study extends the IS literature on expectation confirmation in two ways. First, although much prior research was focused on developing new models of expectation confirmation, the current study is aimed at comparing and addressing inconsistencies among the existing models that offer competing findings. Brown et al. (2008) compared three models of expectation confirmation—namely, the disconfirmation model based on the contrast model, the ideal point model based on the generalized negativity model, and an experiences only model. Comparing these three models using polynomial modeling and response surface methodology, Brown et al. found support for the experiences only model and a modified experiences only model, depending on the expectations/predictors being examined (i.e., ease of use and usefulness, respectively). Brown et al. was an important first step in representing nuances of complex models of expectation disconfirmation in three-dimensional space. However, it is also important to identify and examine other models that have received support in the IS literature and reference fields using even more recent methodological advances in polynomial modeling. More specifically, in addition to the models examined by Brown et al., the current work will examine the assimilation model (Boulding et al. 1993; Szajna and Scamell 1993), assimilation-contrast model (Coughlan and Connolly 2001), and expectations only model (Davis et al. 1989) using first-, second-, and third-order equations. Second, existing research on expectation confirmation has been aimed at developing models to examine a single dependent variable. The goal of the current study is to provide an exemplar of testing multiple relevant dependent variables in a single domain of study. In terms of the dependent variables, we examine behavioral intention, use, and system satisfaction. Although the first two have received extensive attention (see Venkatesh et al. 2003), system satisfaction has also been acknowledged as a key system success metric (Brown et al. 2002; Brown et al. 2008; Delone and McLean 2003; Lankton and McKnight 2012).

Besides the gaps in the IS literature, there are critical gaps in the broad expectation confirmation literature that we aim to fill. Although it is possible that different models may be appropriate for different domains, our review of the expectations confirmation research both in IS and reference disciplines suggests that support for the different models is frequently inferred and sometimes even predicted, but the models have not been *accurately* represented and tested. Our contention is based on the fact that in order to fully articulate and test the tenets of the models, it is important to first remedy several conceptual and measurement issues related to the reliance on linear models and use of difference scores or direct measures of expectation disconfirmation (see Brown et al. 2012; Brown et al. 2008; Venkatesh and Goyal 2010). As we will argue later, the tenets of these models can only be accurately represented using polynomial models and consequently, tested only using polynomial regression analysis. Against this backdrop, the objectives of this research are to:

(1) Discuss the tenets of six models of expectation confirmation and present their analytical representations; and

(2) Empirically examine the support for the models in the context of multiple important dependent variables related to a new IS implementation.

BACKGROUND

Expectation confirmation has been studied in a number of domains, including consumer psychology, organizational behavior, work environment, and IS (for a review, see Kristof-Brown and Guay 2010; Yi 1990) of which some have employed polynomial modeling (see Appendix A for a review). One common thread in this literature on expectation confirmation is that the context dictates the choice of the specific constructs—expectations, experiences, and outcomes. For example, the expectation confirmation paradigm has been widely used in the context of service quality to explain user reactions (e.g., Kettinger and Lee 1994, 2005). Because of the context of service quality, expectations of and experiences with assurance, reliability, empathy, and responsiveness are used as key constructs (see Klein et al. 2009).

A large body of research in IS has focused on the topic of employee acceptance of software (e.g., Ahuja and Thatcher 2005; Compeau and Higgins 1995a, 1995b; Compeau et al. 2007; Compeau et al. 1999; Png et al. 2001; Thatcher and Perrewe 2002; Wells et al. 2010). Consistent with Brown et al. (2008), we reviewed the research on this topic and identified the dominant theoretical model to be the technology acceptance model (TAM; for a review, see Venkatesh et al. 2007). The independent variables in TAM are: perceived usefulness, defined as the degree to which using the software enhances an individual's effectiveness, and perceived ease of use, defined as the degree to which using the software is relatively free from effort (Venkatesh et al. 2003). TAM has been repeatedly tested in a variety of empirical studies (see Venkatesh et al. 2007 for a review), with results fairly consistently demonstrating that perceived usefulness is the primary predictor of intention and use, and perceived ease of use has an effect on intention mediated by perceived usefulness. Thus, in the current work, we examine a priori expectations and a posteriori experiences associated with perceived usefulness as the primary predictor of use. We also include ease of use in our modeling, but consistent with prior work, we adopt the view that it is secondary to usefulness and include it only as a control variable.

In the context of a new IS implementation, behavioral intention, actual use, and satisfaction are considered to be key dependent variables (see Choudhury and Karahanna 2008; Delone and McLean 1992, 2003; McKnight et al. 2002). Behavioral intention has a significant history as an important dependent variable in IS as well as an important predictor of IS use (e.g., Venkatesh et al. 2003). It is important to study IS use because prior research (e.g., Venkatesh and Davis 2000) has shown that organizations fail to accrue benefits of IT investments if users are unwilling to use available systems (see Venkatesh et al. 2003). Low use of installed systems is considered one of the main causes for the "productivity paradox" (see Devaraj and Kohli 2003). Finally, satisfaction has been identified as an important dependent variable, not only when use of the system is mandated (Brown et al. 2002; Tan et al. 2000; Tan et al. 1999; Tan et al. 1994), but also as a general IS success metric (Delone and McLean 2003).

Six theoretical perspectives have been used to understand the relationships among expectations, experiences, and important outcome variables. Anderson (1973) highlighted four models of expectation confirmation: assimilation, contrast, generalized negativity, and assimilation-contrast. Brown et al. (2008) examined an experiences only model in addition to the disconfirmation and ideal point models that are similar to Anderson's (1973) contrast and generalized negativity models respectively. Finally, Hom et al. (1999) examined an expectations only model along with the experiences only model to understand expectation confirmation (see Pulakos and Schmitt 1983).

Anderson (1973) found support for the assimilation-contrast model and concluded that consumers will evaluate a product less favorably when the disparity between expectations and experiences exceeds a certain threshold point. Using polynomial regression analysis (PRA), Brown et al. (2008) found support for an experiences only model in the case of one predictor and a slightly modified experiences only model in the case of a second predictor. They concluded that, as a determinant of satisfaction, in contrast to more complex models of expectation confirmation that have permeated the literature, the role of expectations was minimal and experiences was the dominant driver of satisfaction. Other research has also found that experiences are the key determinant in expectation confirmation (e.g., person-environment fit meta-analysis conducted by Yang et al. 2008). However, Kristof-Brown and Guay (2010) argued that this effect can be attributed to either higher variance in experiences or experiences incorporating expectations.

Beyond the use of a single theoretical model to drive the research, Brown et al. (2008) highlight three main assumptions and methodological gaps in prior empirical research on expectation confirmation that may lead to these conflicting findings (see also Brown et al. 2012; Venkatesh and Goyal 2010). 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 expectations, experiences, and outcome variables (e.g., Edwards and Parry 1993). Second, a number of studies have used difference scores to determine the level of expectation disconfirmation (e.g., French et al.1982). The organizational 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). Some of the key problems associated with the use of difference scores are that they: (1) provide confounding and ambiguous results as it is difficult to understand whether the influence on the outcome variable is caused by expectations, experiences, or a combination of both; (2) oversimplify complex three-dimensional relationship between expectations, experiences, and the outcome into a two-dimensional relationship; and (3) impose several untested constraints that may not be satisfied by an unconstrained equation. Third, recent studies have used direct measurement of disconfirmation in order to circumvent problems associated with the use of 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).

THEORY

In this section, we discuss the theoretical underpinnings of the six models that we examine: assimilation, contrast, generalized negativity, assimilation-contrast, expectations only, and experiences only. Table 1 provides an overview of the six models.

Table 1: Overview of Six Models

Model	**Underlying Theoretical Perspectives**	**Recommendations for Management**	**Examples from IS**
Assimilation	Cognitive dissonance (Festinger 1962)	Overstate expectations	Lankton and McKnight (2012) Szajna and Scamell (1993)
Contrast	Disconfirmation of Expectations (Churchill and Suprenant 1982)	Understate expectations	Staples et al. (2002)

Generalized Negativity	Met expectations hypothesis (Irving and Meyer 1994; Porter and Steers 1973; Wanous 1992) Equity theory (Adams 1963)	Set expectations as accurately as possible	Ginzberg (1981) Tan et al. (1999) Venkatesh and Goyal (2010)
Assimilation-contrast	Cognitive dissonance (Festinger 1962) Disconfirmation of expectations (Churchill and Suprenant 1982)	Set expectations a little high, accurately, or extremely low	Brown et al. (2012)
Expectations Only	No formal theoretical perspective	Expectations are the only things that matter; set them high	Davis et al. (1989)
Experiences Only	No formal theoretical perspective	Expectations are irrelevant; focus on the experience	Brown et al. (2008)

Assimilation Model

Cognitive dissonance theory is the underpinning for the assimilation model. Cognitive dissonance theory (Festinger 1962) argues that deviations from one's expectations create dissonance, which is an uncomfortable state. In order to reduce dissonance, subsequent outcome evaluations are adjusted 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). This theory further argues that actual experiences provide input to outcome evaluations but the outcome evaluations are biased in favor of expectations. Individuals minimize the cognitive difference between expectations and outcomes by adjusting outcome evaluations to be more consistent with expectations, thus reducing dissonance. Based on cognitive dissonance theory, expectations should be overstated in hopes of raising expectations. These higher expectations would lead individuals to adjust their perceptions of their experiences in a positive manner in order to reduce dissonance and result in more positive outcomes.

Support for cognitive dissonance theory 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. Researchers have found similar results with respect to consumer expectations, perceptions, and product evaluations (Hoch and Ha 1986; Olshavsky and Miller 1972; Olson and Dover 1979). Research on employee expectations, experiences, and job satisfaction has also found similar results (e.g., Hoiberg and Berry 1978; Ilgen 1971). Szajna and Scamell (1993) examined the relationship among expectations regarding the actual performance of and satisfaction with an IS. Their experimental design incorporated manipulations of expectations about the system. 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. The underlying rationale is that users who perceive inconsistencies between their expected software use perceptions and experienced software use perceptions would be in a state of psychological discomfort. In order to decrease this inconsistency, these users would alter their perceptions of their experiences with the software use to align with their expectations.

Contrast Model

Disconfirmation of expectations theory is the underpinning for the contrast model. Disconfirmation of expectations theory 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 (Churchill and Suprenant 1982; Patterson et al. 1997). Rather than focus on the expectations, as in cognitive dissonance theory, disconfirmation of expectations theory focuses on the difference between the expectations and the subsequent evaluations (see Brown et al. 2008). The degree to which expectations are exceeded is called positive disconfirmation and the degree to which expectations are unmet is called negative disconfirmation (Bhattacherjee 2001; Kopalle and Lehman 2001). Based on the disconfirmation perspective, high positive disconfirmation results in greater satisfaction whereas high negative disconfirmation results in lower satisfaction (for a review, see Yi 1990). Thus, this perspective offers management recommendations that are opposite to what would be indicated by cognitive dissonance theory and suggests the most favorable outcomes occur when the expectation-experience gap is maximized and experiences exceed expectations.

One stream of research that relies on disconfirmation of expectations theory is realistic job previews (e.g., Philips 1998; Wanous et al. 1992). This stream of research argues that realistic job previews (i.e., when employee expectations are more closely aligned with the job conditions they would encounter) increase employee satisfaction and reduce the likelihood of turnover. The underlying rationale here is that, with realistic job previews, employees are more likely to have their expectations met or exceeded (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 low organizational commitment. Realistic job preview research proposes that lowered expectations should reduce the resulting dissatisfaction that newcomers experiences (Wanous 1992). The results in this stream of research provide evidence in support of the disconfirmation of expectations paradigm. 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 system effectiveness and satisfaction, when compared to those with accurate or low expectations.

Generalized Negativity Model

The met expectations hypothesis is the underpinning for the generalized negativity model. The met expectations hypothesis (Irving and Meyer 1994; Porter and Steers 1973; Wanous 1992) 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). In essence, the met expectations hypothesis argues that there is an ideal point (see Brown et al. 2008) where expectations and experiences are equal and the resulting outcome is highest. A negative evaluation associated with failing to meet expectations is not surprising and is supported by disconfirmation theory. However, a negative impact associated with having expectations exceeded, while not intuitively appealing, does have support 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. Essentially, individuals evaluate the ratio of outcomes to inputs. In the sense of expectations, if individuals expect a specific outcome, they will adjust their inputs accordingly. If, in the end, they feel the outcomes are not in line with their inputs, there is a mismatch. Individuals who receive more than they feel is fair experience guilt or shame associated with the inequity, as they feel they did not earn the outcome. In this sense, having expectations exceeded can have a negative impact. In sum, the met expectations hypothesis would argue for setting expectations accurately to eliminate any deviation, minimize psychological tension, and ultimately maximize satisfaction.

The met expectations hypothesis suggests that the direction of discrepancy does not matter, rather any difference between expectations and experiences is bad. This is supported in research by Rice et al. (1989) who examined the impact of discrepancies between wants and experiences on satisfaction. Although not focused on expectations, the Rice et al. (1989) results support the notion that getting more than one wants can have a negative impact. It seems reasonable that this impact would translate to expectations, as well. In an IS context, Ginzberg (1981) demonstrated that users who held realistic expectations were more satisfied with the resulting system than were users with unrealistic expectations. Likewise, Venkatesh and Goyal (2010) showed that any mismatch between expectations and experiences caused a negative emotional response towards the system.

Assimilation-contrast Model

Cognitive dissonance theory and expectation disconfirmation theory together provide the underpinnings of the assimilation-contrast model (see Anderson 1973). The model proposes that for slight differences, outcome evaluations will assimilate toward expectations, whereas 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 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). 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 disconfirmation theory. The contrast aspect of the assimilation-contrast model argues that large differences, regardless of whether they are negative or positive, will be treated different from small differences. Thus, an assimilation-contrast model suggests that setting expectations slightly high, accurately or extremely low would be preferred to setting them excessively high.

In a study of consumer satisfaction, Anderson (1973) found support for the assimilation-contrast model. Using an experimental design in which participants 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 differences became large, outcomes 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 was within an expected range of outcomes, thus supporting an assimilation-contrast model. In the IS literature, Brown et al. (2012) found that expectations have a direct positive effect on software use as the magnitude of expectation disconfirmation decreases. However, as the magnitude of expectation disconfirmation increases, negative disconfirmation has a negative influence on software use and positive disconfirmation has a positive effect on software use.

Expectations Only and Experiences Only Models

Although not explicitly presented by Anderson (1973), two other models are of interest in understanding the relationship among expectations, evaluations, and a desired outcome: expectations only and experiences only. These models have been supported empirically in prior literature (see Brown et al. 2008; Irving and Meyer 1994) and provide an important benchmark against which more complex models can be compared. In the expectations only model, expectations directly predict outcomes, thus representing a perfect assimilation toward an individual's a priori beliefs. More specifically, outcomes are predicted only by expectations and experiences play no role. It is important to note that in the assimilation model, although experiences are assimilated towards expectations, a perfect assimilation of experiences with expectations may never be achieved. 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. An expectations only view is consistent with the predictions in TAM 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 contrast, Brown et al. (2008) found that experiences play a primary role in determining user satisfaction with software use.

Understanding Competing Results

Across and within domains of study, multiple expectations models have been supported. Brown et al. (2008) propose that the competing results are due to three key factors: (1) the predominant use of linear models and analytical techniques; (2) the use of a difference scores approach to analyses; and (3) the direct measurement of confirmation rather than the measurement of expectations and experiences separately. To address these limitations, Brown et al. propose the use of polynomial modeling and response surface analysis. Polynomial modeling presents an alternative technique for determining the separate and joint contribution of expectations and experiences to an outcome (see Edwards 2002). 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 methodology used in much prior expectation confirmation literature (Edwards 1994). Therefore, to address the methodological shortcomings 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. 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 addition to the issues raised by Brown et al. (2008), we propose that reliance on a single theoretical model to explain the phenomenon of interest further contributes to the competing results. In the majority of studies reviewed, a single model of expectation confirmation is employed. Although 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 control for this variability thus allowing us to test all six models in a single context. Testing competing models in a single study can help us develop a clearer understanding of the conditions under which specific models will hold. In the current 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.

METHOD

In this section, we discuss the context of the study—namely, software acceptance. We also discuss the organizational setting, participants and procedure, and measurement details.

Organizational Setting, Participants, and Data Collection Procedure

Most large organizations today leverage knowledge resources by implementing knowledge management initiatives (Kankanhalli et al. 2005; Kankanhalli et al. 2003). The setting for this study was one such organization, with nearly 8,000 employees, operating in the telecommunication industry. The organization implemented an Intranet-based software system for knowledge sharing among employees. More specifically, the organization's objective with the new software system was to facilitate information sharing among employees, and to serve as a bulletin-board for employees in various departments to share their personal and social interests. The use of the software system was completely voluntary. Traditional systems (e.g., a paper-based system) continued to be available during the entire duration of this study.

Although all 8,000 employees comprised our initial sampling frame, heads of various business units suggested choosing somewhere between 25 and 50% of the employees at random for data collection. Therefore, we revised our sampling frame to 2,400 employees. We contacted these employees by email to solicit their participation in the study. In all, 1,601 completed questionnaires were received in the first wave of data collection. We contacted these 1,601 employees for the second round of data collection and received 1,113 usable responses, resulting in an overall response rate of 46.4%. About a third of the participants in the study were women. The average age was just about 35 (SD ≈ 10). We tested our sample for non-response bias concerns. First, we compared the demographic profiles of the respondents and the sampling frame. We then compared the non-respondents from the first round to the respondents in both rounds. We found that the demographic profiles were similar in all these comparisons. We also conducted different comparisons based on the key constructs in the model and found no appreciable differences between those who responded only in the first round and those who responded in both rounds.

We administered the survey at two different points in time. The organization mandated a training program for all employees on the new system. In this training program, the organization provided hands-on training with the system to all employees over a period of two days. During the training program, employees were also provided information about the potential benefits of the system. The authors did not participate in the training program and thus did not introduce bias into the study by inadvertently setting expectations at a particular level. Moreover, to the best of our knowledge, the organization did not schedule training programs with the intention of setting expectations at a certain level. We administered the first survey immediately after this training (t_1), with a view toward measuring employees' expectations. The second survey was administered six months after the employees had used the system (t_2), with a view toward measuring employees' experiences. Participants returned both surveys within the first week of receiving them. We measured expectations and experiences, operationalized by measuring users' perceptions of usefulness and ease of use towards the system, at time t_1 and time t_2 respectively. This approach is similar to that used in prior research (e.g., Brown et al. 2008). We measured behavioral intention and system satisfaction at t_2. The organization provided access to the software system use (behavior) logs that were used to determine employees' actual use of the system. These logs were available to us for software use for a year starting from t_1. However, we only used the system use data collected in the six month period after t_2 as the dependent variable—this was important because both expectations and experiences are used as predictors in our model.

Measurement

All constructs in this study were measured using items validated in prior research. The items for pre-use expectations and post-use evaluations of perceived usefulness and perceived ease of use were adapted from prior research (e.g., Brown et al. 2008). Seven-point Likert agreement scales were used in conjunction with the items. These items were worded appropriately for measurement at t_1 (immediately after the training) and at t_2 (six months after the system implementation). As noted earlier, we included the three most common dependent variables—namely, behavioral intention, use, and satisfaction—used in IS research to test six competing models of expectation disconfirmation. In order to avoid problems associated with common method and social desirability biases, we used duration of system use (excluding the idle time) as a measure of use. The items for satisfaction were adapted from Brown et al. (2008) and behavioral intention from Venkatesh and Goyal (2010).

In order to provide a baseline model for comparison, we measured the direct disconfirmation of usefulness and ease of use by adapting measures used by Bhattacherjee and Premkumar (2004). Direct measurement involves asking respondents about their level of disconfirmation with the system. Such direct measurement requires respondents to perform a mental comparison of their expectations of a system and actual experiences with the system (Irving and Meyer 1995, 1999). Appendix B lists the items used. Although we strongly advise against the use of difference scores or direct measures to test the various models presented in this research, it is possible to do so; the interested reader is referred to Appendix C for the analytical model specifications and the results associated with these tests.

ANALYTICAL REPRESENTATION OF THEORETICAL MODELS

We use polynomial modeling and response surface analysis to test the various models.

Polynomial Modeling

Traditional analytical techniques are susceptible to problems associated with linear models, difference scores, and direct measures (Edwards 2002; Irving and Meyer 1994, 1995). Polynomial modeling involves examination of an outcome variable by regressing commensurate component measures (i.e., expected and experienced usefulness) along with the successive powers of these measures (Edwards 2002; Edwards and Harrison 1993). Maintaining the distinction between expectations and experiences allows us to separately determine their influence on the outcome variables, thus avoiding problems associated with difference scores and/or direct measures. Furthermore, including successive powers of expectations and experiences in the analysis allows us to evaluate the possibility of complex curvilinear relationships.

This analytical technique may be applied in a confirmatory or exploratory manner (Edwards 2001; Edwards and Parry 1993). The confirmatory procedure begins with the identification of a regression equation corresponding to the conceptual model and the relaxation of constraints that the model specifies. These constraints are then used as hypotheses for falsification of the conceptual model. The model support is determined by the following four conditions: (1) the variance explained by the regression equation corresponding to the conceptual model differs from zero; (2) all the coefficients of the relaxed regression equation follow the appropriate pattern; (3) all the constraints imposed by the model are satisfied; and (4) the variance explained by the higher-order terms (i.e., terms one order higher than the those in the equation) does not differ from zero. For example, an algebraic difference score equation can be shown:

$$Z = b_0 + b_1 (X-Y) + e \text{ (or) } Z = b_0 + b_1X - b_1Y + e \qquad (1)$$

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

$$Z = b_0 + b_1X + b_2Y + e \qquad (2)$$

Support for the theoretical model presented in equation 1 will rest on the following four conditions: (1) variance explained by equation 2 is significantly different from zero; (2) constraints on equation 2 (e.g., $b_2 = - b_1$) are satisfied; (3) the coefficients of regression in equation 2 follow the appropriate pattern; and (4) the variance explained by the regression equation after adding the curvilinear terms (quadratic in this case) does not significantly differ from zero.

Response Surface Methodology

Response surface methodology presents visual and statistical tests to better understand the intricacies of complex polynomial models (Edward and Parry 1993). Often, polynomial models yield higher-order regression equations with coefficients that are difficult to interpret. Response surfaces developed from the higher-order regression equations serve as interpretive frameworks that help us understand these complex polynomial models. There are three key features of the response surface: (1) stationary point: point at which the slope of the surface is zero in all directions; (2) principal axes: set of lines, termed first principal axis and second principal axis, that run perpendicular to each other and intersect at the stationary point—i.e., for convex surfaces, the upward curvature is greatest along the first principal axis and least along the second principal axis, whereas for concave surfaces, the downward curvature is greatest along the second principal axis and least along the first principal axis; and (3) slopes along lines of interest: these lines of interest include the principal axes, the confirmation axis—i.e., line along which expectations = experiences—and the disconfirmation axis—i.e., line along which expectations = - experiences (for a review, see Edwards and Parry 1993; Edwards 2002). It could be argued that disconfirmation occurs when expectations are not equal to experiences. However, in agreement with prior research (e.g., Brown et al. 2008; Edwards and Parry 1993; Venkatesh and Goyal 2010), perfect disconfirmation occurs when expectations are equal to and opposite of experiences.

A key condition for the support of the conceptual model requires that the variance explained by the set of terms one order higher than those in the relaxed regression equation is not significantly different from zero. However, much prior polynomial research (e.g., Edwards 2002; Lambert et al. 2003) has primarily relied only on the linear and second-order polynomial equations. This may be due to the lack of key response surface features, such as stationary points and principal axes, in surfaces implied by third- or higher-order polynomials. However, we argue that models represented by third-order polynomial equations can be tested by using some of the other features of the response surface, such as slopes along the confirmation or disconfirmation axis. For example, a third-order regression equation can be represented 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 = Outcome; U_1 = Experienced usefulness; U_2 = Expected usefulness

Because Experienced usefulness = Expected usefulness (i.e., $U_1 = U_2$) along the confirmation axis, equation 3 can be written as:

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

Similarly, because Experienced usefulness = - Expected usefulness (i.e., $U_1 = - U_2$) along the disconfirmation axis, equation 3 can be written as:

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

Based on equations 4 and 5, we can see 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. These slopes can be used as statistical tests to determine if the response surface along these axes is cubic.

Polynomial modeling requires a two-dimensional relationship (as observed in traditional expectation confirmation models) 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 theoretical models into three-dimensional response surfaces, which we present next. The three-dimensional plots of the theoretical models are presented in Figure 1.

Figure 1: Three-dimensional Plots of the Six Theoretical Models

Figure 1(a): Assimilation Model

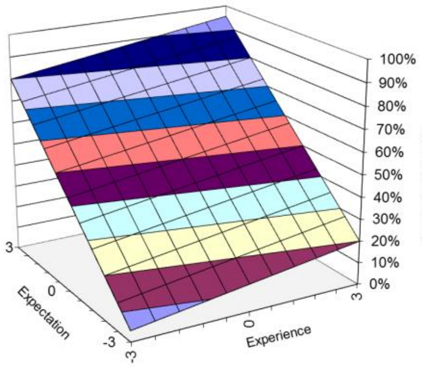


Figure 1(b): Contrast Model

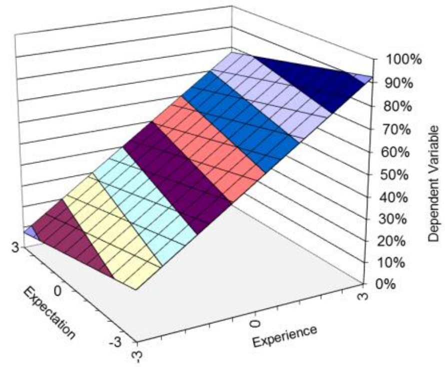


Figure 1(c): Generalized Negativity Model

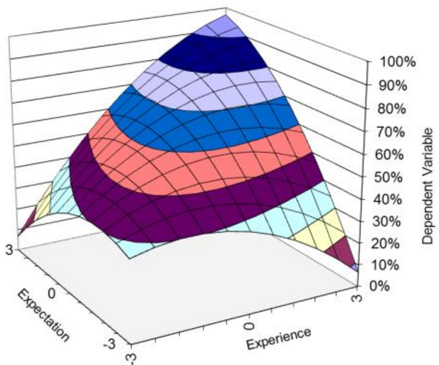


Figure 1(d): Assimilation-contrast Model

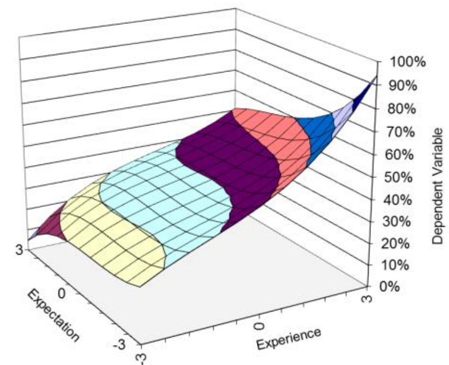


Figure 1(e): Experiences Only Model

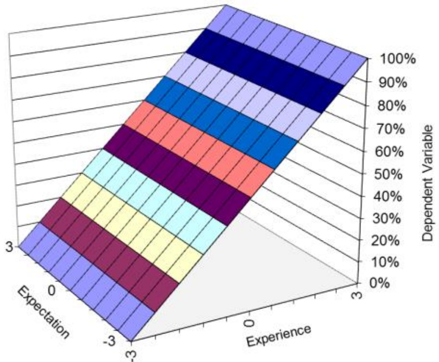
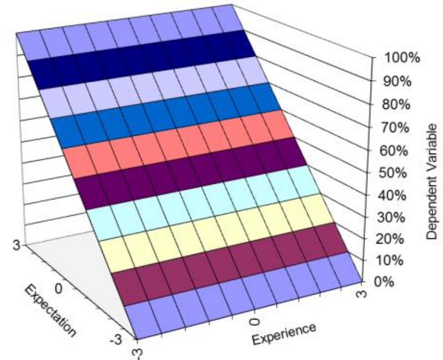


Figure 1(f): Expectations Only Model



Analytical Representations

As it is difficult to directly interpret equations associated with response surfaces, the slopes along the lines of interest—here, the confirmation and 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.

Prior research on software acceptance indicates that high levels of perceived usefulness are preferred when compared to low levels (Venkatesh and Davis 2000). While examining software perceptions within the expectation confirmation framework, high levels of both expectations and experiences of usefulness would result in a higher outcome (e.g., use) than would low levels of expectations and experiences. It has also been observed that desired outcomes are lowest in the low-expectations and low-experiences scenario and highest in the high-expectations and high-experiences scenario (Olshavsky and Miller 1972). Therefore, the value of the outcome 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 a linear slope along the confirmation axis. A positive and linear slope along the confirmation axis would imply the value of a_x will be positive and the values of a_x^2 and a_x^3 will be zero.

The disconfirmation axis is of particular interest because the slope of the response surface along this axis corresponds directly with the slope of the line generated from an analysis of expectation confirmation models using 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 (e.g., Anderson 1973). 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.

Assimilation Model

A psychological state of consonance exists when there is no deviation from one's expectations, whereas a psychological state of dissonance exists when there is a significant deviation from one's expectations (Festinger 1962; Szajna and Scamell 1993). 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 expectations and minimum experiences levels, whereas the right-hand corner of the plot represents a point of minimum expectations and maximum experiences levels. A three-dimensional depiction of the response surface supporting the assimilation model is shown in Figure 1(a) and is represented by the equation:

$$Z = b_0 + b_1U_1 + b_2U_2 + e \qquad (7)$$

Where, Z = Outcome; U_1 = Experienced usefulness; U_2 = Expected usefulness

The assimilation model, based on cognitive dissonance theory, suggests that a higher level of expectations is associated with more favorable outcomes. The level of the outcome variable is biased towards the level of expectations (Szajna and Scamell 1993). Therefore, for a response surface supporting this model, the expectations coefficient (b_2) must necessarily be greater than the experiences coefficient (b_1) and both the coefficients should be positive. Hence, the tests:

Test 1: $b_2 > b_1$

Test 2: $b_1 > 0$ and $b_2 > 0$

Moreover, the value of the outcome 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). In essence, the slope of the disconfirmation axis—i.e., a_y—would be negative, although the absolute value of a_y would be less than the slope of the confirmation axis—i.e., a_x. As noted earlier, the slope of the confirmation axis—i.e., a_x—in all the models would be positive. Hence, the tests:

Test 3: $a_x > 0$; $a_y < 0$

Test 4: $|a_x| > |a_y|$

Contrast Model

The contrast model, based on disconfirmation of expectations theory, suggests that unmatched expectations create a state of disconfirmation (Anderson 1973), and the ultimate outcome evaluations are based on the direction and size of the gap between expectations and experiences or the direction and level of disconfirmation (Sherif and Hovland 1961). Contrary to the assimilation model, the contrast model places more emphasis on experiences. Therefore, use increases as experiences exceed expectations and decreases as experiences falls short of expectations. A three-dimensional depiction of the response surface supporting this model is shown in Figure 1(b) and is represented by the equation:

$$Z = b_0 + b_1U_1 + b_2U_2 + e \qquad (8)$$

Where, Z = Outcome; U_1 = Experienced usefulness; U_2 = Expected usefulness

For the contrast model, experiences have a higher impact on use than expectations do. Thus, the experiences coefficient (b_1) should be higher than the expectations coefficient (b_2). Hence, the test:

Test 1: $|b_1| > |b_2|$

Because the size of the gap between expectations and experiences determines the outcome assessment, high maximum and minimum values of the gap can be achieved by having an opposite sign on the coefficients of U_1 and U_2. Thus, we expect the coefficient of U_1—i.e., b_1—to be positive and the coefficient of U_2—i.e., b_2—to be negative. Moreover, this difference is maximized if the coefficient of U_1 is equal and opposite to the coefficient of U_2. Hence, the tests:

Test 2: $b_1 > 0$; $b_2 < 0$

Test 3: $b_2 = - b_1$

A response surface representing a contrast model would have a higher value of an outcome along the disconfirmation axis at points where experiences are high and expectations are low. As experiences decrease and expectations increase along the disconfirmation axis, the value of the outcome variable will decrease. Therefore, the slope of both the disconfirmation axis and the confirmation axis—i.e., a_y and a_x—would be positive. Hence, the test:

Test 4: $a_x > 0$ and $a_y > 0$

However, the slope of the disconfirmation axis would be higher than the slope of the confirmation axis ($|a_x| < |a_y|$) because positive disconfirmation is associated with a higher level of the outcome (e.g., use). Hence, the test:

Test 5: $|a_x| < |a_y|$

Generalized Negativity Model

The generalized negativity model, based on the met expectations hypothesis, 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). Further, when one's experiences fall short of expectations, a negative disconfirmation results in lower outcome evaluations (e.g., use) and when one's experiences exceed their expectations, a positive disconfirmation results in lower outcome evaluations (Anderson 1973). A three-dimensional depiction of the surface supporting the met expectations hypothesis is shown in Figure 1(c) and can be represented by the following equation:

$$Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + e \quad (9)$$

Where, Z = Outcome; U_1 = Experienced usefulness; U_2 = Expected usefulness

A response surface representing these relationships would have the highest outcome (e.g., use) when there is no mismatch between expectations and experiences—i.e., the confirmation axis. The outcome decreases as expectations exceed experiences or expectations fall short of experiences. In other words, the outcome decreases as we move away from the confirmation axis in either direction. The surface takes on a positive slope when expectations are greater than experiences and a negative slope when experiences are greater than expectations. The slope of the surface changes from positive to negative at the confirmation axis. This 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. Therefore, we expect at least one of the quadratic coefficients (i.e., b_3, b_4, or b_5) to be significantly different from zero. Hence, the test:

Test 1: $|b_3|$, $|b_4|$, or $|b_5| > 0$

As the positive and negative disconfirmation of expectations have equal and opposite effects on the outcome, we expect the linear slope of the disconfirmation axis to be equal to zero and the expectations and experiences coefficients to have approximately the same magnitude. As in other models of expectation disconfirmation (e.g., assimilation model), the linear slope of the surface—i.e., a_x—along the confirmation axis is positive. Hence, the tests:

Test 2: $b_1 = b_2$

Test 3: $a_x > 0$; $a_y = 0$

Moreover, based on principles from basic calculus (e.g., Hoffman et al. 2006; Waner and Costenoble 2007), the change in slope from positive to negative would require the quadratic slope along the disconfirmation axis to be significant and negative. Hence, the test:

Test 4: $a_y^2 < 0$

However, the curvilinear slope of the surface—i.e., a_x^2—along the confirmation axis is equal to zero because outcome evaluations are expected to increase linearly as both expectations and experiences increase. Hence, the test:

Test 6. $a_x^2 = 0$

For a_x^2 to be equal to zero, the sum of the coefficients of the squared experiences and expectations terms—i.e., b_3 and b_5—should be equal and opposite to the coefficient of the product term of expectations and experiences—i.e., b_4 (Edwards and Parry 1993). For a_y^2 to be negative, the sum of the coefficients of the second order terms—i.e., $b_3 - b_4 + b_5$—should be negative (Edwards and Parry 1993). Collectively, these two conditions lead us to expect that the coefficients of the squared expectations and experiences terms—i.e., b_3 and b_5—will be negative and the coefficient of the product of expectations and experiences—i.e., b_4—will be positive. Hence, the test:

Test 7: $b_3 < 0$; $b_4 > 0$; $b_5 < 0$

Assimilation-contrast Model

The assimilation-contrast model takes on properties of both cognitive dissonance theory and disconfirmation of expectations theory, thus resulting in a more complex response surface. When the differences between expectations and experiences are small, outcome evaluations (e.g., use) are determined largely by expectations, consistent with the assimilation model. On the contrary, when differences between expectations and experiences are large, outcome evaluations are determined by the level of the 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:

$$Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + b_6U_1^3 + b_7U_1^2U_2 + b_8U_1U_2^2 + b_9U_2^3 + e \qquad (10)$$

Where, Z = Outcome; U_1 = Experienced usefulness; U_2 = Expected usefulness

Similar to the other models, the differences between experiences 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. Again, based on principles from basic calculus (e.g., Hoffman et al. 2006; Waner and Costenoble 2007), the cubic function along the disconfirmation axis would require a cubic slope—i.e., a_y^3—to be significant and positive and at least one of the cubic coefficients (i.e., b_6, b_7, b_8, or b_9) to be significantly different from zero. Hence, the test:

Test 1: $|b_6|$, $|b_7|$, $|b_8|$, or $|b_9| > 0$

Test 2: $a_y^3 > 0$

Consistent with the other models (e.g., assimilation model), the slope along the confirmation axis should be linear and positive with no curvilinear component. Therefore, the quadratic—i.e., a_x^2—and the cubic—i.e., a_x^3—slope along the confirmation axis should be zero. Hence, the tests:

Test 3: $a_x > 0$

Test 4: $a_x^2 = 0$

Test 5: $a_x^3 = 0$

Finally, for large differences, the assimilation-contrast model does not differentiate between the influence of positive and negative disconfirmation. So, a decrease in the outcome variable for large negative disconfirmation is equal to an increase in the outcome variable for large positive disconfirmation. In other words, the slope of the surface for the positive disconfirmation axis is equal to the slope of the surface for negative disconfirmation. Hence, the test:

Test 6: $a_{y\ (negative\ disconfirmation)} = a_{y\ (positive\ disconfirmation)}$

Experiences Only and Expectations Only Model

The experiences only and expectations only models are included in this study to serve as baseline models for the more complex models. The experiences only model suggests that outcome evaluations are determined entirely by experiences, with only the U_1 coefficient—i.e., b_1—expected to be positive and significant. Hence, the test:

Test 1: $b_1 > 0$

Test 2: $b_2 = 0$

However, the absolute value of the slope for the confirmation and disconfirmation axes should be equal ($|a_x| = |a_y|$) for the experiences only models, thus indicating that there is no interaction between expectations and experiences in the model. Hence, the test:

Test 3: $|a_x| = |a_y|$

Consistent with the other linear models (e.g., contrast model), the slope along the confirmation axis should be positive. The value of the outcome (i.e., behavioral intention, use, and satisfaction) along the disconfirmation axis would be higher in the region where experiences are highest (the right-hand side of the plot) and lower in the region where experiences are lowest (on the left-hand side of the plot). Therefore, the slope of the disconfirmation axis—i.e., a_y—would also be positive. Hence, the tests:

Test 4: $a_x > 0$; $a_y > 0$

Similarly, the expectations only model suggests that the outcome is determined entirely by expectations, with only the U_2 coefficient—i.e., b_2—expected to be positive and significant. Also, like the experiences only model, in the expectations only model, the absolute value of the slope for the confirmation and disconfirmation axes should be equal ($|a_x| = |a_y|$) because there is no interaction between expectations and experiences. Hence, the tests:

Test 1: $b_1 = 0$

Test 2: $b_2 > 0$

Test 3: $|a_x| = |a_y|$

The slope along the confirmation axis should be positive for the expectations only model as outcome variables (i.e., behavioral intention, use, and satisfaction) behave in the same manner when expectations are met as other linear models (e.g., experiences only model) . However, the value of the outcome (i.e., behavioral intention, use, and satisfaction) along the disconfirmation axis would be higher in the region where expectations are highest (the back-side of the plot) and lower in the region where expectations are lowest (on the front-side of the plot). This results in the slope of the disconfirmation axis decreasing as we go from left to right. Therefore, for the expectations only model, the slope of the disconfirmation axis—i.e., a_y—would be negative. Hence, the tests:

Test 4: $a_x > 0$; $a_y < 0$

The expected slopes along the lines of interest, direction of the coefficients, and the tests for all six models of expectation disconfirmation are summarized in Table 2.

Table 2: Slopes and Coefficients

	Coefficients									Slopes along the Lines of Interest						
	U_1	U_2	U_1^2	U_1*U_2	U_2^2	U_1^3	$U_1^2U_2$	$U_1U_2^2$	U_2^3	Confirmation Axis $U_1 = U_2$			Disconfirmation Axis $U_1 = -U_2$			
Model	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	a_x	a_x^2	a_x^3	a_y	a_y^2	a_y^3	**Summary**
Assimilation	+	+								+			-			Test 1: $b_2 > b_1$ Test 2: $b_1 > 0$; $b_2 > 0$ Test 3: $a_x > 0$; $a_y < 0$ Test 4: $\|a_x\| > \|a_y\|$
Contrast	+	-								+			+			Test 1: $\|b_1\| > \|b_2\|$ Test 2: $b_1 > 0$; $b_2 < 0$ Test 3: $b_2 = - b_1$ Test 4: $a_x > 0$; $a_y > 0$ Test 5: $\|a_x\| < \|a_y\|$
Generalized Negativity	+	+	-	+	-					+	0		0	-		Test 1: $\|b_3\|$, $\|b_4\|$, or $\|b_5\| > 0$ Test 2: $b_1 = b_2$ Test 3: $a_x > 0$; $a_y = 0$ Test 4: $a_y^2 < 0$ Test 5: $a_x^2 = 0$ Test 6: $b_3 < 0$; $b_4 > 0$; $b_5 < 0$
Assimilation-contrast	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+	0	0			+	Test 1: $\|b_6\|$, $\|b_7\|$, $\|b_8\|$, or $\|b_9\| > 0$ Test 2: $a_y^3 > 0$ Test 3: $a_x > 0$ Test 4: $a_x^2 = 0$ Test 5: $a_x^3 = 0$ Test 6: $a_{y\,(\text{negative disconfirmation})} = a_{y\,(\text{positive disconfirmation})}$
Experiences Only	+	0								+			+			Test 1: $b_1>0$ Test 2: $b_2 = 0$ Test 3: $\|a_x\| = \|a_y\|$ Test 4: $a_x > 0$; $a_y > 0$
Expectations Only	0	+								+			-			Test 1: $b_1 = 0$ Test 2: $b_2 >0$ Test 3: $\|a_x\| = \|a_y\|$ Test 4: $a_x > 0$; $a_y < 0$

Notes:

1. U_1 = Experienced usefulness; U_2 = Expected usefulness; a_x = linear slope along confirmation axis; a_y = linear slope along disconfirmation axis; a_x^2 = quadratic slope along confirmation axis; a_y^2 = quadratic slope along disconfirmation axis; a_x^3 = cubic slope along confirmation axis; a_y^3 = cubic slope along disconfirmation axis; b_1=coefficient of U_1; b_2=coefficient of U_2; b_3=coefficient of U_1^2; b_4=coefficient of U_1 U_2; b_5=coefficient of U_2^2; b_6=coefficient of U_1^3; b_7=coefficient of U_1^2 U_2; b_8=coefficient of $U_1U_2^2$; and b_9=coefficient of U_2^3.

RESULTS

Preliminary Analysis

As recommended by Edwards (2002), we first screened the data set for any outliers. Using Cook's D and standardized residuals from regression equations, we excluded all the cases that met the minimum criteria set by Bollen and Jackman (1990). In all, we excluded 6 cases. We then calculated the average of scale-centered item measures for perceived usefulness to determine expectations and experiences measures. Scale centering (done by subtracting scale midpoints from actual score) helps reduce problems associated with multicollinearity and also assists in meaningful interpretations of polynomial equation coefficients (Edwards and Harrison 1993, Edwards 2002). As we measured our items using seven-point Likert agreement scales, scale-centered items ranged from -3 to +3. The low value of VIFs (under 4) for all variables, including the higher-order and interaction terms, alleviated concerns associated with multicollinearity. We also conducted Harmon's one-factor test and the partial correlation procedure (see Podsakoff and Organ 1986) to test our data for common method bias. Based on the results of these tests, we concluded that our data does not suffer from common-method bias. Finally, as we used similar items to measure expectations and experiences, we tested for the presence of correlated measurement errors between items. The non-significant Durbin-Watson test statistic ($p > 0.05$) confirmed that our data does not suffer from correlated measurement problem.

We used a jackknife procedure to estimate the significance level of the various components of response surfaces (e.g., slopes along principal axes). 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—non-parametric procedures, such as jackknifing and bootstrapping, are used (Efron and Gong 1983). Because of our large sample size, we had the choice of using either jackknifing or bootstrapping. We followed Edwards and Parry (1993) and used a jackknife procedure. For all analyses, U_1 represents experienced usefulness, U_2 represents the expected usefulness, and Z represents the outcome. The Cronbach alpha coefficients exceed 0.80 for all scales, thus showing adequate reliability. A principal component analysis with varimax rotation of the independent variables yielded a four-factor solution (i.e., expected usefulness, experienced usefulness, expected ease of use, and experienced ease of use) strongly supporting convergent validity. Although the specific results are not shown here, consistent with prior literature (e.g., Brown et al. 2008), all loadings were greater than 0.80 and all cross-loadings were less than 0.30. Further, we found that the means of all scales was close to or above 4 (or 0 after scale-centering) and the standard deviations were above 1. All the constructs were correlated, with the highest correlations being between experienced usefulness and outcome variables, such as use. Because higher-order terms are mathematically calculated from lower-order terms, they are highly correlated. Table 3 shows the descriptive statistics and correlations.

Table 3: Descriptive Statistics and Correlations

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Gender	N/A	N/A													
2	Age	35.92	9.97	.20***												
3	EOU_1	3.90	1.22	.20***	-.23***											
4	EOU_2	4.30	1.30	.23***	-.26***	.05										
5	BI_1	4.48	1.30	.14*	-.24***	-.22***	.25***									
6	Use_{12}	4.22	1.16	.15*	-.15*	.14*	.17**	.38***								
7	Sat_1	4.04	1.28	.19**	-.28***	-.25***	.26***	.33***	.40***							
8	DU	3.10	1.45	.09	-.15*	.25***	.13*	-.23***	-.28***	-.30***						
9	DEOU	2.61	1.39	-.13*	-.14*	-.19**	-.25***	-.14*	-.20**	-.22***	.35***					
10	U_1	3.84	1.17	.16**	-.19**	.25***	.18**	.44***	.50***	.55***	.19**	.16**				
11	U_2	4.43	1.11	.23***	-.21***	.15*	.19**	.29***	.35***	.40***	.19**	.13**	.03***			
12	BI_2	4.55	1.24	.15*	-.28***	-.24***	.26***	.39***	.37***	.35***	-.24***	-.22***	.40***	.50***		
13	Use_{23}	7.43	6.01	.17**	-.19**	.17**	.22***	.33***	.38***	.35***	-.33***	-.24***	.37***	.27***	.35***	
14	Sat_2	3.70	1.44	.20**	-.30***	-.26***	.28***	.30***	.35***	.32***	-.25***	-.22***	.48***	.58***	.35***	.44***

Notes:

1. BI_2: Behavioral Intention measured at t_2; BI_1: Behavioral Intention measured at t_1. Use_{23}: Use measured at from t_2 to t_3; Use_{12}: Use measured from t_1 to t_2. Sat_2: Satisfaction measured at t_2; Sat_1: Satisfaction measured at t_1. EOU_2: Expected ease of use; EOU_1: Experienced ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, BI_1, Use_{12}, Sat_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, BI_2, Use_{23}, Sat_2.
5. $p < .05$; ** $p < .01$; *** $p < .001$.

Model Testing

In order to conduct confirmatory tests of the six models of expectation confirmation, we examined the unconstrained polynomial models (linear, quadratic, and cubic) for perceived usefulness (see Tables 5 through 7). The unconstrained equations explained significant variance in the dependent variables and yielded significant values for the coefficients of U_1 and U_2 for the first-order equations and subsequent higher-order equations. Following the methodology prescribed by Edwards and Parry (1993), the coefficients for each dependent variable (i.e., behavioral intention, use, and satisfaction)[1] were then used to determine slopes along the confirmation and disconfirmation axis (see also, Brown et al. 2012). The methodology presented by Edwards (2002) and Edwards and Parry (1993) is summarized in Appendix D. These slopes along the lines of interest (i.e., confirmation and disconfirmation axes) are summarized in Tables 8 through 10. The coefficients of the regression equations and the slopes along the lines of interest were used to examine the constraints imposed by various models that we discuss next.

Some of the constraints imposed by the assimilation model for perceived usefulness predicting all three outcome variables (i.e., behavioral intention, use, and satisfaction) were satisfied as: (1) the value of both b_1 ($p < .01$) and b_2 ($p < .01$) were positive (test 2); (2) the absolute value of the slope along the confirmation axis was significantly higher ($p < .01$) than the absolute value of the slope along the disconfirmation axis for all three outcome variables (test 4); and (3) the slope along the confirmation axis was positive for all three outcome variables ($a_x = 1.44$, $p < .01$ for BI; $a_x = 1.80$, $p < .01$ for use; and $a_x = 1.95$, $p < .01$ for satisfaction) (test 3). However, this model was not supported for any of the outcome variables because: (1) b_2 was not greater than b_1 for any of the three outcome variables (test 1); (2) the slope along the disconfirmation axis was positive for all three outcome variables ($a_y = 0.56$, $p < .01$ for BI; $a_y = 0.52$, $p < .01$ for use; and $a_y = 0.53$, $p < .01$ for satisfaction) (test 3); and (3) the results of an F-test (p <

[1] Because the regressors in each of the equations are identical, there is no need to use seemingly unrelated regressions.

.01) showed that the variance explained by higher-order (quadratic) terms was substantially higher than the variance explained by first-order terms.

Table 5: Unconstrained Model: Predicting BI_2 Using Usefulness

	First-order Linear Equation			Second-order Quadratic Equation			Third-order Cubic Equation		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.39	-0.13*	0.01	0.58	-0.10	0.04	0.69	-0.02	0.02
Gender		0.22**	0.02		0.25***	0.02		0.05	0.02
EOU_1		0.05	0.01		0.05	0.02		0.10	0.03
EOU_2		0.21**	0.01		0.17*	0.01		0.13*	0.04
BI_1		0.42***	0.03		0.30***	0.03		0.02	0.01
U_1		1.00***	0.08		0.24**	0.10		-0.37**	0.09
U_2		0.44***	0.11		0.22**	0.11		2.41**	0.18
U_1^2					-0.60***	0.10		-0.28***	0.09
U_1U_2					1.41***	0.08		0.78***	0.10
U_2^2					-0.40***	0.08		-0.36***	0.06
U_1^3								0.22***	0.02
$U_1^2U_2$								-0.38***	0.03
$U_1U_2^2$								0.17***	0.01
U_2^3								-0.38***	0.04
				$\Delta R^2 = 0.19$***			$\Delta R^2 = 0.11$***		

Notes:

1. BI_2: Behavioral intention measured at t_2; BI_1: Behavioral intention measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, BI_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, BI_2.
5. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6: Unconstrained Model: Predicting Use_{23} Using Usefulness									
	First-order Linear Equation			Second-order Quadratic Equation			Third-order Cubic Equation		
Independent Variable	R^2	B	SE	R^2	B	SE	R^2	B	SE
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_1U_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
$U_1^2U_2$								-0.43***	0.01
$U_1U_2^2$								0.32***	0.01
U_2^3								-0.40***	0.02
				$\Delta R^2 = 0.16$***			$\Delta R^2 = 0.19$***		

Notes:

1. Use_{23}: Use measured at t_2; Use_{12}: Use measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, Use_{12}, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, Use_{23}.
5. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 7: Unconstrained Model: Predicting Sat_2 Using Usefulness									
	First-order Linear Equation			**Second-order Quadratic Equation**			**Third-order Cubic Equation**		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.38	-0.14*	0.01	0.53	-0.19*	0.01	0.68	-0.10	0.03
Gender		0.20*	0.02		0.29***	0.02		0.08	0.03
EOU_1		0.08	0.05		0.08	0.04		0.04	0.03
EOU_2		0.29***	0.01		0.20*	0.01		0.05	0.03
Sat_1		1.04***	0.07		0.76***	0.08		0.04	0.03
U_1		1.24***	0.05		1.10***	0.04		1.01***	0.04
U_2		0.71**	0.04		0.80***	0.05		1.55***	0.08
U_1^2					0.93***	0.03		0.43***	0.01
U_1U_2					0.88***	0.04		-0.50***	0.03
U_2^2					0.89***	0.04		0.57***	0.03
U_1^3								0.39***	0.02
$U_1^2U_2$								-0.40***	0.02
$U_1U_2^2$								0.44***	0.02
U_2^3								-0.53***	0.03
				$\Delta R^2 = 0.15$***			$\Delta R^2 = 0.15$***		

Notes:

1. Sat_2: Satisfaction measured at t_2; Sat_1: Satisfaction measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, Sat_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, Sat_2.
5. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 8: Values of Slopes along Lines of Interest for Predicting BI Using Usefulness

	Confirmation Axis $U_1 = U_2$			Disconfirmation Axis $U_1 = -U_2$		
Model	a_x	a_x^2	a_x^3	a_y	a_y^2	a_y^3
Assimilation	1.44			0.56		
Contrast	1.44			0.56		
Generalized Negativity	0.46	0.41		0.02	-2.41	
Assimilation-contrast	2.04	0.14	-0.37			1.15
Experiences Only	1.44			0.56		
Expectations Only	1.44			0.56		

Note:
U_1 = Experienced usefulness; U_2 = Expected usefulness; a_x = linear slope along confirmation axis; a_y = linear slope along disconfirmation axis; a_x^2 = quadratic slope along confirmation axis; a_y^2 = quadratic slope along disconfirmation axis; a_x^3 = cubic slope along confirmation axis; and a_y^3 = cubic slope along disconfirmation axis.

Table 9: Values of Slopes along Lines of Interest for Predicting Use Using Usefulness

	Confirmation Axis $U_1 = U_2$			Disconfirmation Axis $U_1 = -U_2$		
Model	a_x	a_x^2	a_x^3	a_y	a_y^2	a_y^3
Assimilation	1.80			0.52		
Contrast	1.80			0.52		
Generalized Negativity	1.95	-0.46		-0.51	-2.42	
Assimilation-contrast	1.68	0.10	-0.17			1.49
Experiences Only	1.80			0.52		
Expectations Only	1.80			0.52		

Note:
U_1 = Experienced usefulness; U_2 = Expected usefulness; a_x = linear slope along confirmation axis; a_y = linear slope along disconfirmation axis; a_x^2 = quadratic slope along confirmation axis; a_y^2 = quadratic slope along disconfirmation axis; a_x^3 = cubic slope along confirmation axis; and a_y^3 = cubic slope along disconfirmation axis.

Table 10: Values of Slopes along Lines of Interest for Predicting Satisfaction Using Usefulness

	Confirmation Axis $U_1 = U_2$			Disconfirmation Axis $U_1 = -U_2$		
Model	a_x	a_x^2	a_x^3	a_y	a_y^2	a_y^3
Assimilation	1.95			0.53		
Contrast	1.95			0.53		
Generalized Negativity	1.90	2.70		0.30	0.94	
Assimilation-contrast	2.56	0.50	-0.10			1.76
Experiences Only	1.95			0.53		
Expectations Only	1.95			0.53		

Note:
U_1 = Experienced usefulness; U_2 = Expected usefulness; a_x = linear slope along confirmation axis; a_y = linear slope along disconfirmation axis; a_x^2 = quadratic slope along confirmation axis; a_y^2 = quadratic slope along disconfirmation axis; a_x^3 = cubic slope along confirmation axis; and a_y^3 = cubic slope along disconfirmation axis.

The constraints imposed by the contrast model were not satisfied for any of the outcome variables (i.e., BI, use, and satisfaction) as: (1) b_2 was positive ($p < .01$) for all three outcome variables (test 2); (2) b_2 was not equal and opposite to b_1 for any of the outcome variables (test 3); and (3) the absolute value of the slope along the confirmation axis was significantly higher ($p < .01$) than that of the disconfirmation axis for all three outcome variables (test 5). Also, based on the F-test results ($p < .01$), the variance explained by higher-order (quadratic) terms was substantially higher than the variance explained by first-order terms. Therefore, the contrast model was not supported.

The three-dimensional representation of the generalized negativity model required a second-order polynomial equation. The results for the second-order polynomial equation were similar for BI, use, and satisfaction. All three quadratic coefficients (i.e., b_3, b_4 and b_5) were significantly ($p < .001$) different from zero for all the outcome variables (test 1). Because the value of b_1 ($p < .01$) was not equal to b_2 ($p < .01$), $b_1 - b_2 \neq 0$ ($p < .01$) for all three outcome variables, thus the second constraint was not satisfied (test 2). The value of the linear slope along the disconfirmation axis for use and satisfaction was significantly different from zero ($a_y = 0.02$, n.s. for BI; $a_y = -0.51$, $p < .01$ for use; $a_y = 0.30$, $p < .01$ for satisfaction; test 3). Therefore, test 3 was only satisfied for predicting BI using usefulness. The non-linear slope along the disconfirmation axis was significant and negative for both BI and use ($a_y^2 = -2.41$, $p < .01$ for BI; $a_y^2 = -2.42$, $p < .01$ for use) but not for satisfaction ($a_y^2 = 0.94$, $p < .01$ for satisfaction) (test 4). However, a significant non-zero value of the curvilinear slope along the confirmation axis for all three outcome variables ($a_x^2 = 0.41$, $p < .01$ for BI; $a_x^2 = -0.46$, $p < .01$ for use; $a_x^2 = 2.70$, $p < .01$ for satisfaction) indicated that test 5 was not satisfied. Finally, the results of an F-test ($p < .01$) showed that the cubic model explained significantly higher variance than the quadratic model for all three outcome variables. Therefore, the generalized negativity model was not supported.

The assimilation-contrast model required a cubic equation. It was observed that most of the constraints imposed by the model were satisfied as: (1) all the coefficients for the cubic terms (b_6, b_7, b_8, and b_9) were significantly different from zero ($p < .01$) (test 1); (2) the cubic slope along the disconfirmation axis for all three outcome variables ($a_y^3 = 1.15$, $p < .01$ for BI; $a_y^3 = 1.49$, $p < .01$ for use; $a_y^3 = 1.76$, $p < .01$ for satisfaction) was significant and fairly large (test 2); and (3) the linear slope along the confirmation axis ($a_x = 2.04$, $p < .01$ for BI; $a_x = 1.68$, $p < .01$ for use; $a_x = 2.56$, $p < .01$ for satisfaction) was significant and positive (test 3). However the quadratic for all three outcome variables ($a_x^2 = 0.14$, $p < .01$ for BI; $a_x^2 = 0.10$, $p < .01$ for use; $a_x^2 = 0.50$, $p < .01$ for satisfaction) and cubic ($a_x^3 = -0.37$, $p < .01$ for BI; $a_x^3 = -0.17$, $p < .01$ for use; $a_x^3 = -0.10$, $p < .01$ for satisfaction) slopes along the confirmation axis, although close to zero, were significant (tests 4 and 5), thus providing weak support. Moreover, we found that the positive influence of positive disconfirmation was less than the negative influence of negative disconfirmation (test 6). In other words, looking at the absolute values of the slope, the linear slope of the surface for negative disconfirmation ($p < .01$) was significantly ($p < .01$) higher than the linear slope of the surface for positive disconfirmation ($p < .01$) (test 6). This indicated that the assimilation-contrast model was partially supported for BI, use, and satisfaction.

Support for experiences only and expectations only models required b_1 or b_2 to be zero respectively (test 1). Because both coefficients were non-zero for all three outcome variables, neither of the two models was supported. Although the slope along the confirmation axis ($a_x = 1.44$, $p < .01$ for BI; $a_x = 1.80$, $p < .01$ for use; $a_x = 1.95$, $p < .01$ for satisfaction) was significant and positive for both the expectations only model and the experiences only model, a negative slope along the disconfirmation axis for all three outcome variables ($a_y = 0.56$, $p < .01$ for BI; $a_y = 0.52$, $p < .01$ for use; $a_y = 0.53$, $p < .01$ for satisfaction) shows that the experiences only model is not supported (test 4). Finally, lack of support for the expectations only and experiences only model was indicated by the F-test results ($p < .01$) that showed the variance explained by higher-order (quadratic) terms was substantially higher than the variance explained by first-order terms. Overall, the results of the confirmatory analysis showed that out of the six competing models of expectation confirmation, assimilation-contrast was the best existing model for all three outcome variables. These test results are summarized in Table 11.

Model	Tests	Results (DV: Behavioral Intention)	Results (DV: Use)	Results (DV: Satisfaction)
Assimilation	1: $b_2 > b_1$ 2: $b_1 > 0$; $b_2 > 0$ 3: $a_x > 0$; $a_y < 0$ 4: $\lvert a_x\rvert > \lvert a_y\rvert$	Not supported Supported Not supported Supported	Not supported Supported Not supported Supported	Not supported Supported Not supported Supported
Contrast	1: $\lvert b_1\rvert > \lvert b_2\rvert$ 2: $b_1 > 0$; $b_2 < 0$ 3: $b_2 = - b_1$; 4: $a_x > 0$; $a_y > 0$; 5: $\lvert a_x\rvert < \lvert a_y\rvert$	Supported; Not supported Not supported Supported Not supported	Supported Not supported Not supported Supported Not supported	Supported Not supported Not supported Supported Not supported
Generalized Negativity	1: $\lvert b_3\rvert$, $\lvert b_4\rvert$, or $\lvert b_5\rvert > 0$; 2: $b_1 = b_2$; 3: $a_x > 0$; $a_y = 0$; 4: $a_y^2 < 0$; 5: $a_x^2 = 0$; 6: $b_3 < 0$; $b_4 > 0$; $b_5 < 0$	Supported Not supported Supported Supported Not supported Supported	Supported Not supported Not supported Supported Not supported Supported	Supported Not supported Not supported Not supported Not supported Not supported
Assimilation-contrast	1: $\lvert b_6\rvert$, $\lvert b_7\rvert$, $\lvert b_8\rvert$, or $\lvert b_9\rvert > 0$; 2: $a_y^3 > 0$; 3: $a_x > 0$; 4: $a_x^2 = 0$; 5: $a_x^3 = 0$; 6: $a_{y\ (\text{negative disconfirmation})} = a_{y\ (\text{positive disconfirmation})}$	Supported Supported Supported Partially supported Partially supported Not supported	Supported Supported Supported Partially supported Partially supported Not supported	Supported Supported Supported Partially supported Partially supported Not supported
Experiences Only	1: $b_1>0$; 2: $b_2 = 0$; 3: $\lvert a_x\rvert = \lvert a_y\rvert$; 4: $a_x > 0$; $a_y > 0$	Not supported Not supported Not supported Supported	Not supported Not supported Not supported Supported	Not supported Not supported Not supported Supported
Expectations Only	1: $b_1 = 0$; 2: $b_2 >0$; 3: $\lvert a_x\rvert = \lvert a_y\rvert$; 4: $a_x > 0$; $a_y < 0$	Not supported Not supported Not supported Not supported	Not supported Not supported Not supported Not supported	Not supported Not supported Not supported Not supported

Note:
U_1 = Experienced usefulness; U_2 = Expected usefulness; a_x = linear slope along confirmation axis; a_y = linear slope along disconfirmation axis; a_x^2 = quadratic slope along confirmation axis; a_y^2 = quadratic slope along disconfirmation axis; a_x^3 = cubic slope along confirmation axis; a_y^3 = cubic slope along disconfirmation axis; b_1=coefficient of U_1; b_2=coefficient of U_2; b_3=coefficient of U_1^2; b_4=coefficient of $U_1 U_2$; b_5=coefficient of U_2^2; b_6=coefficient of U_1^3; b_7=coefficient of $U_1^2 U_2$; b_8=coefficient of $U_1U_2^2$; and b_9=coefficient of U_2^3.

DISCUSSION

We discussed the core tenets of six different theoretical models of expectation confirmation—i.e., assimilation, contrast, generalized negativity, assimilation-contrast, experiences only, and expectations only. We developed the analytical representations of the different models and empirically tested the models in a single context and study to examine the impact of expectations and experiences on three different dependent variables. Our results show that, of these existing models of expectation-confirmation, the assimilation-contrast model was the best in terms of capturing the relationship between expectations and experiences and key outcome variables—i.e., behavioral intention, use, and satisfaction. Interestingly, the results were quite consistent across the different dependent variables. We tested various alternative models, namely, linear, quadratic and cubic, and found that the cubic model explained significantly higher (70%, 68%, and 69% for behavioral intention, use, and satisfaction respectively) variance in key outcome variables.

Theoretical Contributions

This work makes key contributions to expectation confirmation research, a topic that has received much attention in IS. First, our detailed review of prior expectation confirmation models and description of the tenets is a useful starting point for future research on this topic. Second, developing accurate analytical representations of the various models is crucial for future research on this topic. Now, researchers in IS and other fields alike can employ these models by leveraging the current work to conduct accurate empirical tests of the models in their chosen domain of study. Third, our work provides an exemplar of testing multiple expectation confirmation models and examining multiple relevant dependent variables in a single domain of study.

Our results present a richer and more complete understanding of expectation disconfirmation. For example, prior expectation disconfirmation research in IS (see Bhattacherjee and Premkumar 2004) used direct measurement of disconfirmation, a proxy for difference scores (Irving and Meyer 1995), and found that expectation confirmation produces desirable outcomes (e.g., a higher behavioral intention to use a system). Although our findings are consistent with such prior work, our results provide additional insights. We found that the influence of confirmation on the outcome is dependent on the absolute levels of the confirmation. More specifically, we found that only confirmation at high levels of expectations is desirable because the confirmation at low levels of expectations lowers the outcome value (e.g., use). Testing all six competing models in one single study within the same context shows that the assimilation-contrast model has the highest predictive ability and is the best available model for explaining the relationship between usefulness and key dependent variables in IS.

Our results demonstrate that polynomial modeling presents an opportunity to examine curvilinear relationships in expectation-confirmation research in general and drivers of human behavior in particular. Consistent with prior technology acceptance literature (for a review, see Venkatesh et al. 2003), the results of the linear model suggest that higher use is achieved when usefulness experiences are high. The polynomial models, however, provide a much richer explanation, suggesting that certain combinations of pre-use expectations and post-use evaluations lead to differing levels of technology use. These results provide evidence that approaching organizational problems from a linear perspective may yield a limited or even an inaccurate understanding of organizational phenomena.

One aspect of our results that warrants further explanation is the partial support for tests 4 and 5 ($a_x^2 = 0$; $a_x^3 = 0$) of the assimilation-contrast model. We theorized that the slope of quadratic and cubic terms along the confirmation axis for the assimilation contrast model should be zero. However, the results for Tests 4 and 5 indicate that these slopes, although very close to zero, were positive and significant. A small yet positive curvilinear slope represents a slightly U-shaped confirmation axis. This indicates that, in a state of confirmation (expectations = experiences), the value of an outcome (e.g., satisfaction) may decrease slightly before increasing as both expectations and experiences increase from the lowest level to the highest level. One possible explanation for this could be that when users' expectations that the system will not enhance their performance at all (i.e., lowest expectations) are confirmed, they do not expend any effort exploring any additional features of the system. However, when users' expectations that the system will contribute very minimally to enhance their performance are confirmed, they might expend some effort to explore additional features that might result in disappointment, thus resulting in a low level of an outcome. We should, however, be careful in interpreting such small coefficients, as we observed for tests 4 and 5.

Prior IS research has noted that such small coefficients, although statistically significant may not be practically significant (see Chin 1998). Even in reference disciplines, despite significant p-values, Edwards and his colleagues have referred to small coefficients as not sufficiently different from zero (e.g., Edwards 2002, Edwards and Harrison 1993).

Another finding that demands further attention is the lack of support for test 6 in the assimilation-contrast model. Based on the tenets of the assimilation-contrast model (Anderson 1973), we expected negative disconfirmation and positive disconfirmation to have an equal and opposite effect. However, we found that the absolute value of the linear slope along the disconfirmation axis was stronger for negative disconfirmation than it was for positive disconfirmation. More specifically, we found that the negative influence of negative disconfirmation had a stronger impact on user evaluations than the positive influence of positive disconfirmation. In the context of a new IS implementation, this finding has three implications. First, when users of a new IS perceive increasing differences between expectations and experiences, there is a point at which these differences will cause a strong influence on evaluations of the new IS. This influence may be positive or negative, depending on the direction of the disconfirmation. Second, when users perceive a positive surprise, such that they find the system to be much better than they had expected, they will have positive evaluations of the system. However, because users' expectations from the new IS were not high, they may not spend the extra effort in exploring various features the new IS may offer. Therefore, although user evaluations are positive, they may not be very strong. Finally, when users' experiences fall below their expectations, users will view the new IS unfavorably and will have negative evaluations of the IS. In such a scenario, it is likely that users are unable to find some of the useful features that they expected and they may choose not to use the useful features that they do expect and find in the new IS. Therefore, negative disconfirmation has a much stronger impact than positive disconfirmation does on IS evaluations.

Taken together, the findings and contributions of this study provide a mechanism for addressing the limitations in much prior expectation confirmation research. First, as four of the six models that we examined theorize non-linear relationships, we accurately represent the theoretical models and go beyond the use of linear models, contrary to what much prior research has done. Second, by keeping expectations and experiences separate in the conceptualization, measurement and analyses, we remedy concerns associated with the use of difference scores (expectations – experiences) and direct conceptualization/measurement of confirmation/disconfirmation (e.g., a question asks about the extent of confirmation, thus requiring the participant to perform a cognitive comparison of expectations and experiences). By addressing these limitations, we did not find support for five models widely used in the expectation confirmation literature (i.e., assimilation, contrast, generalized negativity, expectations only, and experiences only). The assimilation-contrast model was only partially supported. This highlights the complex relationship between expectations and experiences and how they collectively influence outcomes, such as behavioral intention, use and satisfaction. These complex relationships, when oversimplified, could result in distorted or erroneous conclusions.

In the current study, the same model was relevant for each of the three dependent variables—behavioral intention, use, and satisfaction. Although we expected some variations in the findings due to the differences across prior studies, it is possible that context is a more important factor than the dependent variable in determining model relevance. For example, in the technology acceptance context, it is difficult to believe that someone would be dissatisfied by getting a system that exceeded his or her expectations. Yet, it is possible to believe that if someone feels they are unjustifiably promoted or overpaid, there could be shame or guilt associated with having expectations exceeded. Thus, the differences we see in prior research could be due to variation in context. Brown et al. (2002) provide evidence that a change in dependent variable is appropriate when examining technology acceptance in mandatory, as opposed to volitional, contexts. Further evidence of the importance of a mandatory context is demonstrated in the findings of Brown et al. (2008), where the results for a model with satisfaction as the dependent variable conform most closely to an experiences only model. For technology acceptance, the nature of use may be an important factor in assessing model relevance. When looking across expectations studies in IS, we see a combination of dependent variables and contexts. By holding the context constant, the current work begins to shed light on what does (and does not) impact model relevance. Future research is clearly needed to delve deeper into the relationship between context and dependent variable selection in determining model relevance.

Limitations and Future Research Directions

Our study has two limitations that should be noted. First, polynomial regression analysis is based on the assumptions of ordinary least squares that the independent variables are measured without error. Also, with the decrease in the reliabilities of measures, coefficient estimates can be biased. Because polynomial regression analysis involves the use of higher-order terms, these problems may be even more pronounced. In our study, high reliabilities of all measures (> 0.80) considerably limit the likelihood of these biases. In any case, we recommend that future research replicate this study. Second, we used a six-month interval between the measurements of expectations and experiences. Although this time difference allowed us to measure expectations and experiences separately and reduce the influence of the new software implementation shakedown, it might raise some questions about potential biases. Hogan (1987), for example, suggests that raters might put too much weight on negative information in order to reduce uncertainty. This may result in raters reporting ratings lower than warranted. Again, replication of this study would help alleviate such concerns by providing support for the generalizability of our findings.

The results of the current study highlight the idea that future research should continue to use polynomial models to re-examine other organizational phenomena that incorporate expectations and actual evaluations—e.g., negotiation (Barry and Oliver 1996; Oliver et al. 1994), job design (Ganster et al. 2001), person-job fit (Saks and Ashforth 1997) and person-organization fit (Cable and Judge 1996; Kristof 1996).

Future research should also examine existing models of expectation-disconfirmation and their relationships with other dependent variables, such as organizational commitment (O'Reilly and Chatman 1986) and turnover intentions (Huselid and Day 1991). In doing so, researchers should examine why the use of different dependent variables results in different models being more relevant.

Future research should also examine how cross-cultural differences may affect the interplay between expectations and experiences. Prior research has shown that national cultural values may influence attitude towards a product and product use (Srite and Karahanna 2006). Several studies have argued that IS adoption may be affected by national culture (e.g., Keil et al. 2000; Tan et al.1998; Tan et al. 2003). Further, because of increasing globalization and advances in communication technologies, there have been several calls for testing the applicability of theories across various cultures (Kankanhalli et al. 2007; Tan 2007; Tan et al. 1998). Cross-cultural studies examining the influence of expectations and experiences on IS outcomes could be valuable. As an example, future research could study a global organization implementing an IS (e.g., an ERP system) that is influencing its operations in countries with different cultures (e.g., China, US). Comparing the results across different cultures will help to highlight the role of culture in expectation disconfirmation and will further enhance our understanding of this important phenomenon.

Although the context of our study was IS acceptance, these findings might have implications for researchers dealing with other domains, both within IS, such as online consumer behavior, and outside IS, such as realistic job previews (see Hom et al. 1999). In the context of online consumer behavior, there is a rich body of research that examines the role of several different predictors and their impacts (e.g., Featherman et al. 2006;). In each of these cases, instead of taking a snapshot view (or expectations only view or experiences only view), the models suggested here could be applied to see how the interplay of different predictors (expectations and experiences) will affect key outcomes. Shifting gears to realistic job previews, that literature has demonstrated that setting expectations at a realistic level reduces turnover

(Wanous et al. 1992). The realistic job previews literature also suggests that lower expectations are more easily met and exceeded resulting in higher satisfaction and lower turnover (Lee et al. 1992; Wanous 1992). However, our findings indicate that setting lower expectations may adversely influence behavior. It is likely that lower expectations may lower new employee morale negatively inhibiting their productivity, relationships with other employees, and satisfaction, resulting in turnover. Again, it is possible that these findings may be specific to the context studied in this research. Therefore, future research should examine the generalizability of these findings.

Prior expectation confirmation research in IS (e.g., Bhattacherjee 2001; Staples et al. 2002; Szajna and Scamell 1993) has used a wide variety of expectations, such as usefulness, ease of use, information quality, decision making, knowledge of the system, personal benefit and attitudes concerning use. There is a possibility that different types of expectations might have different influences on the dependent variable being examined (e.g., technology use). However, prior research has indicated that at least for negative disconfirmation, these differences might be minimal (see Staples et al. 2002). Moreover, because the goal of our study was to test and compare six competing models of expectation disconfirmation, using a single type of expectations allows us to test all six models simultaneously in a single context—i.e., a new IS implementation. Future research should replicate the findings of the current study with a different set of expectations. Future research should also test these models in other contexts commonly used in IS research, such as decision making and online shopping (e.g., Koufaris 2002). Examining competing models of expectation confirmation in different contexts would allow for richer theoretical development. Moreover, such an examination would provide us with boundary conditions that define applicability of various models of expectation confirmation.

Practical Implications

This research has four implications for practice. First, our results suggest that managers set realistic expectations and strive to achieve them. If managers think they would err in setting expectations, we suggest that they err on the lower side because exceeding expectations is likely to have a positive effect. This is even more important considering our finding that the negative influence of negative disconfirmation is stronger than the positive influence of positive disconfirmation. One way this can be accomplished is through sharing pre-development prototypes of new systems with users (e.g., Davis and Venkatesh 2004). The pre-prototypes have the advantage of providing fairly accurate portrayals of systems without the significant cost investment associated with development. For systems that have been developed, the more accurately managers can portray the system and how it works, the more likely positive outcomes will be achieved.

Second, we recommend that managers avoid setting extremely low expectations. A common recommendation in the classical marketing literature is to under-promise and over-deliver (Olshavsky and Miller 1972). Even when the system has the potential to make significant improvements in employees' job performance, some managers choose to set extremely low expectations. These managers believe that user reactions will be very positive when these extremely low expectations are positively disconfirmed. Although the assimilation-contrast model supports setting expectations low when managers are in doubt, it is possible that setting unrealistically low expectations could have negative effects. Setting unrealistically low expectations might reduce employee interest in the software. Using polynomial regression analysis allowed us to determine the influence of meeting or exceeding expectations at a low level (i.e., when both expectations and experiences are low) versus meeting or exceeding expectations at a high level (i.e., when both expectations and experiences are high). For the assimilation-contrast model, we found that user evaluations are higher when user expectations are confirmed at a higher level than when user expectations are confirmed at a low level. In other words, even when user expectations were confirmed or even exceeded, if the user expectations are set extremely low, user evaluations are likely to be low. For example, in the context of the current study, extremely low expectations might lead users to avoid expending effort to explore the features of the new software. This avoidance could ultimately result in lower user evaluations of the experience.

Third, we suggest that managers communicate with their employees on a regular basis to assess their experiences. This is consistent with Massey et al.'s (2001) recommendation to communicate throughout the change process associated with IS implementations. Their focus, however, was on management communicating with users. We expand their suggestion to ensure that the communication is also coming from the users to managers. In this way, managers can receive early indications of unmet expectations. Managers may also consider using a decision support tool in which polynomial regression analysis is embedded in order to monitor user experiences. For example, after a system upgrade, managers would be able to assess the degree to which user expectations are met and the resulting impact on important attitudes and behaviors. This could inform communication regarding the current and future system upgrades. Finally, we recommend managers provide maximum possible information to users while training them on a new IS. Such information plays a critical role in developing user expectations about the new IS. If the users are not provided sufficient information, they may either assume the missing information or get this information from other sources, such as their colleagues (see Sykes et al. 2009). If this information that users assume or acquire from other sources is incorrect, it may result in developing unrealistic expectations. Because expectations play such a crucial role in user evaluations, developing unrealistic evaluations could be detrimental to the success of a new IS.

CONCLUSIONS

This work sought to discuss six different expectation confirmation models, develop analytical representations of each of the models, and empirically test them in the context of a new IS implementation. We examined the relationship among pre-implementation expectations, post-implementation experiences, and three key outcomes (dependent variables), namely behavioral intention, use, and satisfaction, using polynomial representations of various expectation confirmation models. The resulting polynomial models provided a richer explanation of the underlying relationship among expectations, experiences, and outcomes than difference scores or linear models did. This work led to key insights into the role of expectations and experiences in the IS implementation context, as well as another piece of evidence supporting the use of polynomial regressions to understand organizational phenomena. Finally, the analytical representations developed in this work will serve as a springboard for future research on different phenomena using expectation confirmation models.

REFERENCES

Adams, J. S. 1963. "Toward an Understanding of Inequity," *Journal of Abnormal Psychology* (67:5), pp. 422-436.

Ahuja, M. K., and Thatcher, J. B. 2005. "Moving Beyond Intentions and Toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use," *MIS Quarterly* (29:3), pp. 429-461.

Anderson, R. E. 1973. "Consumer Dissatisfaction: The Effect of Disconfirmed Expectancy on Perceived Product Performance," *Journal of Marketing Research* (10:1), pp. 38-44.

Aronson, E., and Carlsmith, J. M. 1962. "Performance Expectancy as a Determinant of Actual Performance," *Journal of Abnormal and Social Psychology* (65:3), pp. 178-182.

Atwater, L. E., Ostroff, C., Yammarino, F. J., and Fleenor, J. W. 1998. "Self-Other Agreement: Does It Really Matter?," *Personnel Psychology* (51:3), pp. 577-598.

Bailey, X., and Fletcher, C. 2002. "The Impact of Multiple Source Feedback on Management Development: Findings from a Longitudinal Study," *Journal of Organizational Behavior* (23), pp. 853-867.

Barry, B., and Oliver, R. L. 1996. "Affect in Dyadic Negotiation: A Model and Propositions," *Organizational Behavior and Human Decision Process* (67:2), pp. 127-143.

Berry, L. L., and Parasuraman, A. 1991. *Marketing Services: Competing Through Quality*, New York, NY: Free Press.

Bhattacherjee, A. 2001. "Understanding Information System Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), pp. 351-370.

Bhattacherjee, A., and Premkumar, G. 2004. "Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test," *MIS Quarterly* (28:2), pp. 229-254.

Bollen, K. A., and Jackman, R. 1990. "Regression Diagnostics: An Expository Treatment of Outliers and Influential Cases," in *Modern Methods of Data Analysis*, J. Fox and J. Scottlong (eds.), Newbury Park, CA: Sage Publications, pp. 257-291.

Bono, J. E., and Colbert, A. E. 2005. "Understanding Responses to Multi-Source Feedback: The Role of Core Self-Evaluations," *Personnel Psychology* (58), pp. 171-203.

Boulding, W., Kalra, A., Staelin, R., and Zeithaml, V. A. 1993. "A Dynamic Process Model of Service Quality: From Expectations to Behavioral Intentions," *Journal of Marketing Research* (30:1), pp. 7-27.

Brown, S. A., Massey, A. P., Montoya-Weiss, M. M., and Burkman, J. R. 2002. "Do I Really Have To? User Acceptance of Mandated Technology," *European Journal of Information Systems* (11:4), pp. 283-295.

Brown, S. A., Venkatesh, V., and Goyal. S. 2012. “Expectation Confirmation in Technology Use,” *Information Systems Research* (23:2), pp. 474-487.
Brown, S. A., Venkatesh, V., Kuruzovich, J. N., and Massey, A. P. 2008. “Expectation Confirmation: An Examination of Three Competing Models,” *Organizational Behavior and Human Decision Processes* (105:1), pp. 52-66.
Cable, D. M., and Judge, T. A. 1996. “Person-Organization Fit, Job Choice Decisions, and Organizational Entry,” *Organizational Behavior and Human Decision Processes* (67:3), pp. 294-311.
Cadotte, E. R., Woodruff, R. B., and Jenkins, R. L. 1987. “Expectations and Norms in Models of Consumer Satisfaction,” *Journal of Marketing Research* (24:3), pp. 305-314.
Carlsmith, J. M., and Aronson, E. 1963. “Some Hedonic Consequences of the Confirmation and Disconfirmation of Expectancies,” *Journal of Abnormal and Social Psychology* (66:2), pp. 151-156.
Chin, W. 1998. “Issues and Opinion on Structural Equation Modeling,” *MIS Quarterly* (22:1), pp. 7-16.
Choudhury, V., and Karahanna, E. 2008. “The Relative Advantage of Electronic Channels: A Multidimensional View,” *MIS Quarterly* (32:1), pp. 179-200.
Churchill Jr., G. A., and Surprenant, C. 1982. “An Investigation into the Determinants of Customer Satisfaction,” *Journal of Marketing Research* (19:4), pp. 491-504.
Cohen, J., Cohen, P., West, S. G., and Aiken, L. S. 2003. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (3rd ed.), Mahwah, NJ: Lawrence Erlbaum Associates.
Compeau, D. R., and Higgins, C. A. 1995a. “Application of Social Cognitive Theory to Training for Computer Skills,” *Information Systems Research* (6:2), pp. 118-143.
Compeau, D. R., and Higgins, C. A. 1995b. “Computer Self-Efficacy: Development of a Measure and Initial Test,” *MIS Quarterly* (19:2), pp. 189-211.
Compeau, D. R., Higgins, C. A., and Huff, S. 1999. “Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study,” *MIS Quarterly* (23:2), pp. 145-158.
Compeau, D. R., Meister, D. B., and Higgins, C. A. 2007. “From Prediction to Explanation: Reconceptualizing and Extending the Perceived Characteristics of Innovating,” *Journal of the Association for Information Systems* (8:8), pp. 409-439.
Coughlan, R., and Connolly, T. 2001. “Predicting Affective Responses to Unexpected Outcomes,” *Organizational Behavior and Human Decision Processes* (85:2), pp. 211-225.
Davis, F. D. 1989. “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology,” *MIS Quarterly* (13:3), pp. 319-340.
Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. 1989. “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models,” *Management Science* (35:8), pp. 982-1003.
Davis, F. D., and Venkatesh, V. 2004. “Toward Preprototype User Acceptance Testing of New Information Systems: Implications for Software Project Management,” *IEEE Transactions on Engineering Management* (51:1), pp. 31-46.
DeLone, W. H., and McLean, E. R. 2003. “The DeLone and McLean Model of Information Systems Success: A Ten Year Update,” *Journal of Management Information Systems* (19:4), pp. 9-30.
DeLone, W. H., and McLean, E. R. 1992. “Information Systems Success: The Quest for the Dependent Variable,” *Information Systems Research* (3:1), pp. 60-95.
Devaraj, S., and Kohli, R. 2003. “Performance Impacts of Information Technology: Is Actual Usage the Missing Link?,” *Management Science* (49:3), pp. 273-289.
Dineen, B. R., VandeWalle, D., and Noe, R. A. 2005. “Job Seeker Goal Orientation and the Relative Weighing of P-O and Demands-Abilities Fit Perceptions in Making Applicant Decisions,” in *Proceedings of the 20th Annual Meeting of the Society for Industrial and Organizational Psychology*, Los Angeles, CA.
Dugoni, B. L., and Ilgen, D. R. 1981. “Realistic Job Previews and the Adjustment of New Employees,”

Academy of Management Journal (24:3), pp. 579-591.
Edwards, J. R., and Cable, D. M. 2009. "The Value of Value Congruence," *Journal of Applied Psychology* (94:3), pp. 654-677.
Edwards, J. R. 2002. "Alternatives to Difference Scores: Polynomial Regression Analysis and Response Surface Methodology," in *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis,* F. Drasgow and N. Schmidt (eds.), San Francisco, CA: Jossey-Bass/Pfeiffer, pp. 350-400.
Edwards, J. R. 2001. "Ten Difference Score Myths," *Organizational Research Methods* (4:3), pp. 265-287.
Edwards, J. R. 1994. "Regression Analysis as an Alternative to Difference Scores," *Journal of Management* (20:3), pp. 683-689.
Edwards, J. R., and Harrison, R. V. 1993. "Job Demands and Worker Health: Three-Dimensional Reexamination of the Relationship between Person-Environment Fit and Strain," *Journal of Applied Psychology* (78:4), pp. 628-648.
Edwards, J. R., and Parry, M. E. 1993. "On the Use of Polynomial Regression Equations as an Alternative to Difference Scores in Organizational Research," *Academy of Management Journal* (36:6), pp. 1577-1613.
Edwards, J. R., and Rothbard, N. P. 1999. "Work and Family Stress and Well-Being: An Examination of Person-Environment Fit in the Work and Family Domains," *Organizational Behavior and Human Decision Processes* (77:2), pp. 85-129.
Efron, B., and Gong, G. 1983. "A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation," *The American Statistician* (37:1), pp. 36-48.
Featherman, M. S., Valacich, J. S., and Wells, J. D. 2006. "Is that Authentic or Artificial? Understanding Consumer Perceptions of Risk in E-Service Encounters," *Information Systems Journal* (16:2), pp. 107-134.
Festinger, L. 1962. *A Theory of Cognitive Dissonance*, Stanford, CA: Stanford University Press.
French, J. R. P., Caplan, R. D., and Harrison, R. V. 1982. *The Mechanisms of Job Stress and Strain*, London: Wiley.
Ganster, D. C., Fox, M. L., and Dwyer, D. J. 2001. "Explaining Employees' Health Care Costs: A Prospective Examination of Stressful Job Demands, Personal Control, and Physiological Reactivity," *Journal of Applied Psychology* (86:5), pp. 954-964.
Ginzberg, M. J. 1981. "Early Diagnosis of MIS Implementation Failure: Promising Results and Unanswered Questions," *Management Science* (27:4), pp. 459-478.
Greenhaus, J. H., Seidel, C., and Marinis, M. 1983. "The Impact of Expectations and Values on Job Attitudes," *Organizational Behavior and Human Performance* (31:3), pp. 394-417.
Heng, C. S., Tan, B. C. Y., and Wei, K. K. 2003. "De-escalation of Commitment in Software Projects: Who Matters? What Matters?" *Information and Management* (41:1), pp. 99-110.
Hetch, T. D., and Allen, N. J. 2005. "Exploring Links between Polychronicity and Well-Being from the Perspective of Person-Job Fit: Does it Matter If You Prefer to Do Only One Thing at a Time?" *Organizational Behavior and Human Decision Processes* (98:2), pp. 155-178.
Hoch, S. J., and Ha, Y. W. 1986. "Consumer Learning: Advertising and the Ambiguity of Product Experience," *Journal of Consumer Research* (13:2), pp. 221-233.
Hoffman, L. D., Bradley, G. L., and Rosen, K. H. 2006. *Applied Calculus for Business, Economics, and the Social and Life Sciences*, Columbus, OH: McGraw-Hill.
Hogan, E. A. 1987. "Effects of Prior Expectations on Performance Ratings: A Longitudinal Study," *Academy of Management Journal* (30:2), pp. 354-368.
Hoiberg, A., and Berry, N. H. 1978. "Expectations and Perceptions of Navy Life," *Organizational Behavior and Human Performance* (21:2), pp. 130-145.

Hom, P. W., Griffeth, R. W., Palich, L. E., and Bracker, J. S. 1999. "Revisiting Met Expectations as a Reason Why Realistic Job Previews Work," *Personnel Psychology* (52:1), pp. 97-112.

Huselid, M. A., and Day, N. E. 1991. "Organizational Commitment, Job Involvement, and Turnover: A Substantive and Methodological Analysis," *Journal of Applied Psychology* (76:3), pp. 380-391.

Ilgen, D. R. 1971. "Satisfaction with Performance as a Function of the Initial Level of Expected Performance and the Deviation from Expectations," *Organizational Behavior and Human Performance* (6:3), pp. 345-361.

Irving, P. G., and Meyer, J. P. 1999. "On Using Residual Difference Scores in the Measurement of Congruence: The Case of Met Expectations Research," *Personnel Psychology* (52:1), pp. 85-86.

Irving, P. G., and Meyer, J. P. 1995. "On Using Direct Measures of Met Expectations: A Methodological Note," *Journal of Management* (21:6), pp. 1159-1175.

Irving, P. G., and Meyer, J. P. 1994. "Reexamination of the Met-Expectations Hypothesis: A Longitudinal Analysis," *Journal of Applied Psychology* (79:6), pp. 937-949.

Johns, G. 2006. "The Essential Impact of Context on Organizational Behavior," *Academy of Management Review* (31:2), pp. 396-408.

Johnston, R. 1995. "The Zone of Tolerance: Exploring the Relationship between Service Transactions and Satisfaction with the Overall Service," *International Journal of Service Industry Management* (6:2), pp. 46-61.

Kankanhalli, A., Tan, B. C. Y., and Wei, K. K. 2007. "Managing Conflict in Global Virtual Teams," *Journal of Management Information Systems* (24:3), pp. 237-274.

Kankanhalli, A., Tan, B. C. Y., and Wei, K. K. 2005. "Contributing Knowledge to Electronic Knowledge Repositories: An Empirical Investigation," *MIS Quarterly* (29:1), pp. 113-143.

Kankanhalli, A., Tanudidjaja, F., Sutanto, J., and Tan, B. C. Y. 2003. "The Role of IT in Successful Knowledge Management Initiatives," *Communications of the ACM* (46:9), pp. 69-73.

Keil, M., Mann, J., and Rai, A. 2000. "Why Software Projects Escalate: An Empirical Analysis and Test of Four Theoretical Models," *MIS Quarterly* (24:4), pp. 631-664.

Kennedy, J. R., and Thirkell, P. C. 1988. "An Extended Perspective on the Antecedents of Satisfaction," *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior* (1), pp. 2-9.

Kettinger, W., and Lee, C. 2005. "Zones of Tolerance: Alternative Scales for Measuring Information Systems Service Quality," *MIS Quarterly* (29:4), pp. 607-623.

Kettinger, W., and Lee, C. 1994. "Perceived Service Quality and User Satisfaction with the Information Services Function," *Decision Sciences* (25:5/6), pp. 737-766.

Kim, S. K., and Hsieh, P. H. 2003. "Interdependence and Its Consequences in Distributor-Supplier Relationships: A Distributor Perspective through Response Surface Approach," *Journal of Marketing Research* (40:1), pp. 101-112.

Klein, J. G. 1999. "Developing Negatives: Expectancy Assimilation and Contrast in Product Judgments," *Advances in Consumer Research* (26:1), pp. 463-468.

Klein, G., Jiang, J. J., and Cheney, P. 2009. "Resolving Difference Score Issues in Information Systems Research," *MIS Quarterly* (33:4), pp. 811-826.

Kopalle, P. K., and Lehman, D. R. 2001. "Strategic Management of Expectations: The Role of Disconfirmation Sensitivity and Perfectionism," *Journal of Marketing Research* (38:3), pp. 386-394.

Kotter, J. P. 1973. "The Psychological Contract: Managing the Joining-Up Process," *California Management Review* (15:3), pp. 91-99.

Koufaris, M. 2002. "Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior," *Information Systems Research* (13:2), pp. 205-223.

Kreiner, G. E. 2006. "Consequences of Work-Home Segmentation or Integration: A Person-Environment Fit Perspective," *Journal of Organizational Behavior* (27), pp. 485-507.

Kristof, A. L. 1996. “Person-Organization Fit: An Integrative Review of its Conceptualizations, Measurement, and Implications,” *Personnel Psychology* (49:1), pp. 1-49.
Kristof-Brown, A. L., and Guay, R. P. 2010. “Person-Environment Fit,” In *APA Handbook of Industrial and Organizational Psychology, Volume 3*, S. Zedeck (eds.), Washington, DC: American Psychological Association, pp. 3-50.
Kristof-Brown, A. L., and Stevens, C. 2001. “Goal Congruence in Project Teams: Does the Fit between Members’ Personal Mastery and Performance Goals Matter?,” *Journal of Applied Psychology* (86:6), pp. 1083-1095.
Lambert, L. S., Edwards, J. R., and Cable, D. M. 2003. “Breach and Fulfillment of the Psychological Contract: A Comparison of Traditional and Expanded Views,” *Personnel Psychology* (56:4), pp. 895-935.
Lankton, N. K., and McKnight, H. D. 2012. “Examining Two Expectation Disconfirmation Theory Models: Assimilation and Asymmetry Effects,” *Journal of the Association for Information Systems* (13:2), pp. 88-115.
Lee, T. W., Ashford, S. J., Walsh, J. P., and Mowday, R. T. 1992. “Commitment Propensity, Organizational Commitment, and Voluntary Turnover: A Longitudinal Study of Organizational Entry Processes,” *Journal of Management* (18:1), pp. 15-32.
Liljander, V., and Strandvik, T. 1993. “Estimating Zones of Tolerance in Perceived Service Quality and Perceived Service Value,” *International Journal of Service Industry Management* (4:2), pp. 6-28.
Lubatkin, M. H., Simsek, Z., Ling, Y. and Veiga, J. F. 2006. “Ambidexterity and Performance in Small- to Medium-Sized Firms: The Pivotal Role of Top Management Team Behavioral Integration,” *Journal of Management* (32:5), pp. 646–72.
Massey, A. P., Montoya-Weiss, M. M., and Holcom, K. 2001. “Re-engineering the Customer Relationship: Leveraging Knowledge Assets at IBM,” *Decision Support Systems* (32:2), pp. 155-170.
McKnight, D. H., Choudhury, V., and Kacmar, C. 2002. “The Impact of Initial Consumer Trust on Intentions to Transact with a Web Site: A Trust Building Model,” *Journal of Strategic Information Systems* (11:3-4), pp. 297-323.
Miceli, M. P. 1986. “Effects of Realistic Job Previews on Newcomer Affect and Behavior: An Operant Perspective,” *Journal of Organizational Behavior Management* (8:1), pp. 73-88.
Oh, W., and Pinsonneault, A. 2007. “On the Assessment of the Strategic Value of Information Technologies: Conceptual and Analytic Approaches,” *MIS Quarterly* (31:2), pp. 239-265.
Oliver, R. L. 1980. “A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions,” *Journal of Marketing Research* (17:4), pp. 460-469.
Oliver, R. L. 1977. “Effect of Expectation and Disconfirmation on Postexposure Product Evaluations: An Alternative Interpretation,” *Journal of Applied Psychology* (62:4), pp. 480-486.
Oliver, R. L., Balakrishnan, P. V. S., and Barry, B. 1994. “Outcome Satisfaction in Negotiation: A Test of Expectancy Disconfirmation,” *Organizational Behavior and Human Decision Processes* (60:2), pp. 252-275.
Olshavsky, R. W., and Miller, J. A. 1972. “Consumer Expectations, Product Performance, and Perceived Product Quality,” *Journal of Marketing Research* (9:1), pp. 19-21.
Olson, J. C., and Dover, P. A. 1979. “Disconfirmation of Consumer Expectations through Product Trial,” *Journal of Applied Psychology* (64:2), pp. 179-189.
O’Reilly, C., and Chatman, J. 1986. “Organizational Commitment and Psychological Attachment: The Effects of Compliance, Identification, and Internalization on Prosocial Behavior,” *Journal of Applied Psychology* (71:3), pp. 492-499.
Patterson, P. G., Cicic, M., and Shoham, A. 1997. “A Temporal Sequence Model of Satisfaction and Export Intentions of Service Firms,” *Journal of Global Marketing* (10:4), pp. 23-43.

Phillips, J. M. 1998. “Effects of Realistic Job Previews on Multiple Organizational Outcomes: A Meta-analysis,” *Academy of Management Journal* (41:6), pp. 673-690.

Png, I. P. L., Tan, B. C. Y., and Wee, K. L. 2001. “Dimensions of National Culture and Corporate Adoption of IT Infrastructure,” *IEEE Transactions on Engineering Management* (48:1), pp. 36-45.

Podsakoff, P. M., and Organ, D. W. 1986. “Self-Reports in Organizational Research: Problems and Prospects,” *Journal of Management* (12:4), pp. 531-544.

Porter, L. W., and Steers, R. M. 1973. “Organizational, Work, and Personal Factors in Employee Turnover and Absenteeism,” *Psychological Bulletin* (80:2), pp. 151-176.

Pulakos, E. D., and Schmitt, N. 1983. “A Longitudinal Study of a Valence Model Approach for the Prediction of Job Satisfaction of New Employees,” *Journal of Applied Psychology* (68:2), pp. 307-312.

Rice, R. W., McFarlin, D. B., and Bennett, D. E. 1989. “Standards of Comparison and Job Satisfaction,” *Journal of Applied Psychology* (74:4), pp. 591-598.

Saks, A. M., and Ashforth, B. E. 1997. “A Longitudinal Investigation of the Relationships between Job Information Sources, Applicant Perceptions of Fit, and Work Outcomes,” *Personnel Psychology* (50:2), pp. 395-426.

Shaw, J. D., and Gupta, N. 2004. “Job Complexity, Performance, and Well-Being: When Does Supplies-Values Fit Matter?,” *Personnel Psychology* (57), pp. 847-879.

Sherif, M., and Hovland, C. I. 1961. *Social Judgment: Assimilation and Contrast Effects in Communication and Attitude Change*, New Haven, CT: Yale University Press.

Sherif, M., and Sherif, C. W. 1967. “Attitudes as the Individual’s Own Categories: The Social Judgment Approach to Attitude Change,” in *Attitude, Ego-involvement, and Change*, C. W. Sherif and M. Sherif (eds.), New York: Wiley, pp. 105-139.

Staples, D. S., Wong, I., and Seddon, P. B. 2002. “Having Expectations of Information Systems Benefits that Match Received Benefits: Does IT Really Matter?,” *Information and Management* (40:2), pp. 115-131.

Srite, M., and Karahanna, E. 2006. “The Role of Espoused National Cultural Values in Technology Acceptance,” *MIS Quarterly* (30:3), pp. 679-704.

Sykes, T. A., Venkatesh, V., and Gosain, S. 2009. “Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees' System Use," *MIS Quarterly* (33:2), pp. 371-393.

Szajna, B., and Scamell, R. W. 1993. “The Effects of Information System User Expectations on Their Performance and Perceptions,” *MIS Quarterly* (17:4), pp. 493-516.

Tan, B. C. Y. 2007. “Leveraging Virtual Communities for Global Competitiveness,” *Journal of Global Information Management* (15:3), pp. 1-4.

Tan, B. C. Y., Raman, K. S., and Wei, K. K. 1994. “An Empirical Study of the Task Dimension of Group Support System,” *IEEE Transactions on Systems, Man, and Cybernetics* (24:7), pp. 1054-1060.

Tan, B. C. Y., Smith, H. J., Keil, M., and Montealegre, R. 2003. “Reporting Bad News about Software Projects: Impact of Organizational Climate and Information Asymmetry in an Individualistic and a Collectivistic Culture," *IEEE Transactions on Engineering Management* (50:1), pp. 64-77.

Tan, B. C. Y., Wei, K. K., Huang, W. W., and Ng, G. N. 2000. “A Dialogue Technique to Enhance Electronic Communication in Virtual Teams,” *IEEE Transactions on Professional Communication* (43:2), pp. 153-165.

Tan, B. C. Y., Wei, K. K., Sia, C. L., and Raman, K. S. 1999. “A Partial Test of the Task-Medium Fit Proposition in a Group Support System Environment,” *ACM Transactions on Computer-Human Interaction* (6:1), pp. 47-66.

Tan, B. C. Y., Wei, K. K., Watson, R. T., Clapper, D. L., and McLean, E. R. 1998. “Computer-Mediated Communication and Majority Influence: Assessing the Impact in an Individualistic and a Collectivistic Culture,” *Management Science* (44:9), pp. 1263-1278.

Thatcher, J. B., McKnight, D. H., Baker, E. W., Arsal, R. E., and Roberts, N. H. 2011. "The Role of Trust in Postadoption IT Exploration: An Empirical Examination of Knowledge Management Systems," *IEEE Transactions on Engineering Management* (58:1), pp. 56-70.
Thatcher, J. B., and Perrewe, P. 2002. "An Empirical Examination of Traits as Antecedents to Computer Self-Efficacy and Computer Anxiety," *MIS Quarterly* (26:4), pp. 381-396.
Titah, R., and Barki, H. 2009. "Nonlinearities between Attitude and Subjective Norms in Information Technology Acceptance: A Negative Synergy?," *MIS Quarterly* (33:4), pp. 827-844.
Venkatesh, V., and Davis, F. D. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Management Science* (46:2), pp. 186-204.
Venkatesh, V., Davis, F. D., and Morris, M. G. 2007. "Dead or Alive? The Development, Trajectory and Future of Technology Adoption Research," *Journal of the Association for Information Systems* (8:4), pp. 267-286.
Venkatesh, V., and Goyal, S. 2010. "Expectation Disconfirmation and Technology Adoption: Polynomial Modeling and Response Surface Analysis," *MIS Quarterly* (34:2), pp. 281-303.
Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.
Waner, S., and Costenoble, S. 2007. *Applied Calculus*, Mason, OH: Brooks Cole.
Wanous, J. P. 1992. *Organizational Entry: Recruitment, Selection, Orientation, and Socialization of Newcomers*, Reading, MA: Addison-Wesley.
Wanous, J. P., Poland, T. D., Premack, S. L., and Davis, K. S. 1992. "The Effects of Met Expectations on Newcomer Attitudes and Behaviors: A Review and Meta-Analysis," *Journal of Applied Psychology* (77:3), pp. 288-297.
Wells, J. D., Campbell, D. E., Valacich, J. S., and Featherman, M. 2010. "The Effect of Perceived Novelty on the Adoption of Information Technology Innovations: A Risk/Reward Perspective," *Decision Sciences* (41:4), pp. 813-843.
Yang, L-Q, Levine, E. L., Smith, M. A., Ispas, D., and Rossi, M. E. 2008. "Person-Environment Fit or Person Plus Environment: A Meta-Analysis of Studies Using Polynomial Regression Analysis," *Human Resource Management Review* (18:4), pp. 311-321.
Yi, Y. 1990. *A Critical Review of Consumer Satisfaction*, Chicago, IL: American Marketing Association.

APPENDIX A: STUDIES USING POLYNOMIAL MODELING IN INFORMATION SYSTEMS AND REFERENCE FIELDS

Paper Reference	Discipline	Theory
Atwater et al. (1998)	Personnel Psychology	Self-other agreement
Bailey and Fletcher (2002)	Organizational Behavior	Management competence
Brown et al. (2008)	Organizational Behavior	Expectation confirmation
Brown et al. (2012)	Information Systems	Expectation confirmation
Bono and Colbert (2005)	Psychology	Job performance
Dineen et al. (2005)	Management	Integrative theory
Edwards (1994)	Organizational Behavior	Person-environment fit
Edwards and Cable (2009)	Psychology	Person-environment fit
Edwards and Harrison (1993)	Management	Person-environment fit
Edwards and Parry (1993)	Management	Person-environment fit
Edwards and Rothbard (1999)	Organizational Behavior	Person-environment fit
Hetch and Allen (2005)	Organizational Behavior	Person-job fit
Hom et al. (1999)	Personnel Psychology	Realistic job preview
Irving and Meyer (1994)	Psychology	Met expectation hypothesis
Irving and Meyer (1995)	Personnel Psychology	Met expectation hypothesis
Irving and Meyer (1999)	Personnel Psychology	Met expectation hypothesis
Kim and Hsieh (2003)	Marketing	Distributor-supplier relationships
Klein et al. (2009)	Information Systems	IS service quality
Kristof-Brown and Guay (2010)	Psychology	Person-environment fit
Kristoff-Brown and Stevens (2001)	Psychology	Person-environment fit
Kreiner (2006)	Organizational Behavior	Person-environment fit
Lambert et al. (2003)	Personnel Psychology	Psychological contract theory
Lubatkin et al. (2006)	Management	Behavioral integration
Oh and Pinsonneault (2007)	Information Systems	Resource-centered and contingency-based view
Shaw and Gupta (2004)	Personnel Psychology	Person-environment fit
Titah and Barki (2009)	Information Systems	Economic theory of complementarities
Venkatesh and Goyal (2010)	Information Systems	Expectation confirmation
Yi (1990)	Marketing	Expectation confirmation

APPENDIX B

All items were measured using a 7-point Likert scale with the endpoints strongly disagree to strongly agree, unless noted otherwise.

Expectation items

Usefulness

I expect that <system> will enable me to accomplish tasks more quickly.
I expect that <system> will improve the quality of the work I do.
I expect that <system> will make it easier to do my job.
I expect that <system> will enhance my effectiveness on the job.
I expect that <system> will give me greater control over my job.
I expect that <system> will improve my productivity.

Ease of Use

I expect that it will be easy to get <system> to do what I want it to do.
I expect that overall,<system> will be easy to use.
I expect that learning to operate <system> will be easy for me.
I expect that interacting with <system> will not require a lot of my mental effort.

Experience items

Usefulness

<system> enables me to accomplish tasks more quickly.
<system> improves the quality of the work I do.
<system> makes it easier to do my job.
<system> enhances my effectiveness on the job.
<system> gives me greater control over my job.
<system> improves my productivity.

Ease of Use

It is easy to get <system> to do what I want it to do.
Overall, <system> is easy to use.
Learning to operate <system> is easy for me.
Interacting with <system> does not require a lot of my mental effort.

Satisfaction

I am an enthusiastic user of <system>.
All things considered, my continuing to use <system> in my job is . . . (Extremely Negative to Extremely Positive).
All things considered, my continuing to use <system> in my job is . . . (Extremely Bad to Extremely Good)
All things considered, my continuing to use <system> in my job is . . . (Extremely Harmful to Extremely Beneficial).

Behavioral Intention

I intend to continue using the <system>.
I predict I would continue using the <system>.
I plan to continue using the <system>.

Disconfirmation items

Usefulness

Compared to my initial expectations, the ability of <system>:

To improve my performance was (much worse than expected … much better than expected).

To increase my productivity was (much worse than expected … much better than expected).

To enhance my effectiveness was (much worse than expected … much better than expected).

Ease of use

Compared to my initial expectations:

It was easy to get <system> to do what I want it to do (much worse than expected … much better than expected).

Overall, <system> was easy to use (much worse than expected … much better than expected).

Learning to operate <system> was easy for me (much worse than expected … much better than expected).

Interacting with <system> did not require a lot of my mental effort (much worse than expected … much better than expected).

APPENDIX C. MODEL SPECIFICATIONS USING DIFFERENCE SCORES AND DIRECT MEASURES

Much prior expectation disconfirmation research has either used difference scores or direct measurement models to examine the relationship among expectations, experiences, and outcome variables. Below, we briefly explain these models and present the results of these models using our empirical data.

Table C1: Summary of Model Tests

Theoretical Model	Tests	Model Tests
Assimilation	Algebraic difference Direct Measurement	$Z = b_0 + b_1 (X - Y)$ $Z = b_0 + b_1 (D)$
Contrast	Algebraic difference Direct Measurement	$Z = b_0 + b_1 (X - Y)$ $Z = b_0 + b_1 (D)$
Generalized Negativity	Squared difference Squared Direct Measurement	$Z = b_0 + b_1 (X - Y)^2$ $Z = b_0 + b_1 (D)^2$
Assimilation-contrast	Cubic difference Cubic Direct Measurement	$Z = b_0 + b_1 (X - Y)^3$ $Z = b_0 + b_1 (D)^3$

Notes:
D: Direct measure of disconfirmation; Z: Outcome; X: Experience; Y: Expectation; b1: coefficient of the difference score or the direct measure of the difference score

Difference Score Models

Based on the nature of the relationship (linear or curvilinear), Edwards and Harrison (1993) and Edwards (2002) describe the use of two types of difference score models: (1) algebraic difference where $Z = b_0 + b_1 (X - Y) + e$; and (2) squared difference: $Z = b_0 + b_1 (X - Y)^2$. Edwards (2002) also presents an absolute difference model where $Z = b_0 + b_1 (1 - 2W)(X - Y) + e$ with $W = 0$ when $X > Y$ and $W = 1$ when $X < Y$ or $Z = b_0 + b_1X - b_1Y - 2b_1WX + 2b_1WY + e$, but this model is rarely used. Edwards (2002) argues that these difference score models distort the true relationship between component measures (i.e., X and Y) that may result in oversimplified or erroneous results (for a review, see Edwards 2002).

Direct Measurement Models

In order to avoid the problems with difference scores, Irving and Meyer (1994, 1995, 1999) discussed prior research that used direct measurement models, where the difference between X and Y (component measures) was directly measured instead of being computed. Irving and Meyer (1994, 1995,

1999) illustrate that direct measurement models not only suffer from problems associated with difference scores, but also create additional problems (see Venkatesh and Goyal 2010).

Model Testing: Linear Models

Because the assimilation model and the contrast model are both linear models represented by the equation $Z = b_0 + b_1U_1 + b_2U_2 + e$, their constrained models can also be represented by an algebraic difference model and a linear direct measurement model. Recall that the assimilation model requires expectations to be a dominant predictor of the outcome whereas the contrast model requires experience to be a dominant predictor of the outcome. Therefore, we expect the coefficient of the difference score (experience – expectations) and the direct measure to be negative for the assimilation model and positive for the contrast model.

The results of the constrained difference scores model for all three dependent variables (i.e., BI, use, and satisfaction) are presented in tables C2-C4. The results of the constrained direct measurement model for all three dependent variables (i.e., BI, use, and satisfaction) are presented in table C5. The coefficient of the difference score (BI: 0.30, $p < .01$; use: 0.24, $p < .01$; and satisfaction: 0.24, $p < .001$) is positive for all three dependent variables indicating that the assimilation model is not supported by the difference score model. The coefficient of the direct measure (BI: 0.24, $p < .001$; use: 0.23, $p < .001$; and satisfaction: 0.23, $p < .001$) is also positive for all three dependent variables indicating that the assimilation model is not supported by the direct measurement model. Edwards (2002) explains that for a constrained model to support a theoretical model, an unconstrained model should not explain higher variance in the outcome variable than the constrained model. Because the variance explained by the constrained models—i.e., difference scores and direct measurement models—is significantly less than the variance explained by an unconstrained linear model (see Tables 5-7), both assimilation and contrast models are rejected. Moreover, significantly higher variance explained by the curvilinear difference scores and direct measurement models (see Tables C2-C5) provides further evidence that both assimilation and contrast models are rejected.

Model Testing: Curvilinear Models

As the generalized negativity model involves a second-order curvilinear relationship and is represented by the following equation: $Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + e$, this model can be tested by the squared difference model and the direct measurement model where a squared term of the direct measurement term would be used. Recall that the generalized negativity model requires that the outcome variable is maximized when expectations are equal to experiences. As differences between expectations and experiences increases, the outcome variable decreases. Therefore, we expect the coefficient of the squared difference score term and the squared difference score term to be negative and significant. As presented in tables C2-C4, the coefficient of the difference score (BI: 0.07, n.s.; use: 0.16, $p<.05$; and satisfaction: 0.13, $p<.05$) and the direct measure (BI: 0.23, $p<.001$; use: 0.13, $p<.05$; and satisfaction: 0.14, $p<.05$) were positive for all three dependent variables indicating that the assimilation model is not supported. Moreover, the unconstrained model explained more variance ($R^2 = 0.58$ for BI; $R^2 = 0.51$ for Use; $R^2 = 0.53$ for Sat) than the constrained model, providing further evidence that the assimilation model is not supported.

Finally, the assimilation-contrast model involves a third-order curvilinear relationship because of two inflection points and is represented by $Z = b_0 + b_1U_1 + b_2U_2 + b_3U_1^2 + b_4U_1U_2 + b_5U_2^2 + b_6U_1^3 + b_7U_1^2U_2 + b_8U_1U_2^2 + b_9U_2^3 + e$. This model can be tested by a cubic difference model and the direct measurement model where a cubic term of the direct measurement term would be used. This model is not tested by Edwards (2002) but would follow the same line of reasoning as the squared difference model and will be represented by $Z = b_0 + b_1 (X – Y)^3$. Recall that for the assimilation-contrast model, outcome is explained by expectations for small differences in expectations and experiences and outcome is explained by experiences for large differences in expectations and experiences. Such a relationship is represented by a wave-shaped graph along the X-Y axis which requires the coefficient of $(U_1-U_2)^3$ and their direct measure to be significant. As presented in tables C2-C4, the coefficient of the difference score (BI: 0.08, n.s.; use: 0.12, p<.05; and satisfaction: 0.07, n.s.) and the direct measure (BI: 0.13, p<.05; use: 0.13, p<.05; and satisfaction: 0.16, p<.05) were either not significant or marginally significant. Moreover, the unconstrained model explained more variance (R^2 = 0.69 for BI; R^2 = 0.70 for Use; R^2 = 0.68 for Sat) than the constrained model, providing further evidence that the assimilation-contrast model is not supported.

Table C2: Constrained Model: Predicting BI_2 Using Difference Scores									
	Difference Scores Model			**Squared Difference Scores Model**			**Cubic Difference Scores Model**		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.35	-0.12*	0.01	0.37	-0.12*	0.01	0.38	-.10	.02
Gender		0.21**	0.02		0.21**	0.02		0.20**	0.02
EOU_1		0.08	0.03		0.08	0.03		0.07	0.04
EOU_2		0.20**	0.01		0.22**	0.02		0.21**	0.02
BI_1		0.46***	0.03		0.44***	0.02		0.43***	0.02
$(U_1 - U_2)$		0.30***	0.07		0.24***	0.08		0.21**	0.07
$(U_1 - U_2)^2$					0.07	0.05		0.04	0.05
$(U_1 - U_2)^3$								0.08	0.03
ΔR^2				0.02*			0.01		

Notes:

1. BI_2: Behavioral intention measured at t_2; BI_1: Behavioral intention measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
2. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
3. Variables measured at time t_1: EOU_2, U_2, BI_1, Gender, and Age.
4. Variables measured at time t_2: EOU_1, U_1, BI_2.
5. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table C3: Constrained Model: Predicting Use_{23} Using Difference Scores									
	Difference Scores Model			**Squared Difference Scores Model**			**Cubic Difference Scores Model**		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.37	-0.07	0.02	0.40	-0.05	0.02	0.42	-0.04	0.01
Gender		0.23**	0.02		0.21**	0.02		0.20**	0.02
EOU_1		0.07	0.03		0.06	0.03		0.04	0.04
EOU_2		0.22**	0.03		0.21**	0.02		0.20**	0.02
Use_{12}		0.43***	0.06		0.40***	0.06		0.35***	0.06
$(U_1 - U_2)$		0.24**	0.06		0.20*	0.08		0.17*	0.08
$(U_1 - U_2)^2$					0.16*	0.03		0.14*	0.03
$(U_1 - U_2)^3$								0.12*	0.02
ΔR^2				0.03*			0.02*		

Notes:

6. Use_{23}: Use measured at t_2; Use_{12}: Use measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
7. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
8. Variables measured at time t_1: EOU_2, U_2, Use_{12}, Gender, and Age.
9. Variables measured at time t_2: EOU_1, U_1, Use_{23}.
10. * p < .05; ** p < .01; *** p < .001.

Table C4: Constrained Model: Predicting Sat_2 Using Difference Scores

	Difference Scores Model			Squared Difference Scores Model			Cubic Difference Scores Model		
Independent Variable	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
Age	0.35	-0.13*	0.01	0.41	-0.12*	0.01	0.42	-0.12*	0.01
Gender		0.24*	0.05		0.20*	0.06		0.17*	0.07
EOU_1		0.06	0.05		0.04	0.05		0.03	0.06
EOU_2		0.33***	0.01		0.30***	0.01		0.28***	0.02
Sat_1		0.80***	0.06		0.76***	0.06		0.73***	0.05
$(U_1 - U_2)$		0.24***	0.03		0.20*	0.07		0.17*	0.07
$(U_1 - U_2)^2$					0.13*	0.02		0.12*	0.02
$(U_1 - U_2)^3$								0.07	0.02
ΔR^2					0.06***			0.01	

Notes:

6. Sat_2: Satisfaction measured at t_2; Sat_1: Satisfaction measured at t_1; EOU_1: Experienced ease of use; EOU_2: Expected ease of use; U_1 = Experienced usefulness; U_2 = Expected usefulness.
7. Control variables: EOU_1, EOU_2, Gender (1 represents women), and Age.
8. Variables measured at time t_1: EOU_2, U_2, Sat_1, Gender, and Age.
9. Variables measured at time t_2: EOU_1, U_1, Sat_2.
10. * $p < .05$; ** $p < .01$; *** $p < .001$

Table C5: Constrained Model: Predicting BI_2, Use_{23}, Sat_2 Using Direct Measures										
		Direct Measurement Model			Squared Direct Measurement Model			Cubic Direct Measurement Model		
Dependent Variable	**Independent Variables**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**	**R^2**	**B**	**SE**
BI_2	Age	0.33	-0.15*	0.02	0.41	-0.12*	0.02	0.46	-0.07	0.04
	Gender		0.25***	0.02		0.21***	0.02		0.15*	0.03
	DEOU		-0.21***	0.03		-0.17*	0.03		-0.14*	0.03
	BI_1		0.46***	0.02		0.38***	0.02		0.35***	0.02
	DU		0.24***	0.02		0.21***	0.02		0.17*	0.03
	DU^2					0.23***	0.03		0.20**	0.03
	DU^3								0.13*	0.02
	ΔR^2				0.08***			0.05**		
Use_{23}	Age	0.31	-0.07	0.02	0.35	-0.05	0.03	0.38	-0.04	0.03
	Gender		0.22**	0.02		0.20**	0.03		0.17*	0.03
	DEOU		-0.13*	0.02		-0.12*	0.02		-0.12*	0.03
	Use_{12}		0.42***	0.03		0.40***	0.03		0.35***	0.03
	DU		0.23***	0.02		0.20***	0.02		0.17**	0.02
	DU^2					0.13*	0.04		0.12*	0.04
	DU^3								0.13*	0.03
	ΔR^2				0.04*			0.03*		
Sat_2	Age	0.33	-0.13*	0.01	0.37	-0.12*	0.02	0.41	-.0.10	0.03
	Gender		0.23**	0.02		0.21**	0.02		0.17**	0.03
	DEOU		0.22**	0.04		0.20**	0.04		0.17**	0.04
	Sat_1		0.77***	0.04		0.70***	0.05		0.66***	0.05
	DU		0.23***	0.02		0.21***	0.03		0.19**	0.03
	DU^2					0.14*	0.04		0.10	0.05
	DU^3								0.16*	0.02
	ΔR^2				.04*			0.04*		

Notes:

1. DU = Disconfirmation of usefulness; DEOU = Disconfirmation of ease of use; BI_1: Behavioral intention measured at t_1; BI_2: Behavioral intention measured at t_2; Sat_1: Satisfaction measured at t_1; Sat_2: Satisfaction measured at t_2; ; Use_{12}: Use measured at t_1; Use_{23}: Use measured at t_2
2. Control variables: DEOU, Gender (1 represents women), and Age.
3. Variables measured at time t_1: DEOU, DU, $BI_{1,}$ $Use_{12,}$ $Sat_{1,}$ Gender, and Age.
4. Variables measured at time t_2: $BI_{2,}$ $Use_{23,}$ Sat_2.
5. p<.05; ** p<.01; *** p<.001.

APPENDIX D: SLOPES ALONG LINES OF INTEREST

(Brown et al. 2012; Edwards 2002; Edwards and Parry 1993)

A **linear equation** can be presented by:
$Z = b_0 + b_1X + b_2Y + e$
Slopes along lines of interest for such a linear equation are given by:
Confirmation axis (X = Y line):
Linear slope (a_x) is given by: $b_1 + b_2$
Disconfirmation axis (X = -Y line):
Linear slope (a_y) is given by: $b_1 - b_2$

A **quadratic equation** can be presented by:
$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + e$
Slopes along lines of interest for such a quadratic equation are given by:
Confirmation axis (X = Y line):
Linear slope (a_x) is given by: $b_1 + b_2$
Quadratic slope (a_x^2) is given by: $b_3 + b_4 + b_5$
Disconfirmation axis (X = -Y line):
Linear slope (a_y) is given by: $b_1 - b_2$
Quadratic slope (a_y^2) is given by: $b_3 - b_4 + b_5$

A **cubic equation** can be presented by:
$Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4XY + b_5Y^2 + b_6X^3 + b_7X^2Y + b_8XY^2 + b_9Y^3 + e$
Slopes along lines of interest for such a cubic equation are given by:
Confirmation axis (X = Y line):
Linear slope (a_x) is given by: $b_1 + b_2$
Quadratic slope (a_x^2) is given by: $b_3 + b_4 + b_5$
Cubic slope (a_x^3) is given by: $b_6 + b_7 + b_8 + b_9$
Disconfirmation axis (X = -Y line):
Linear slope (a_y) is given by: $b_1 - b_2$
Quadratic slope (a_y^2) is given by: $b_3 - b_4 + b_5$
Cubic slope (a_y^3) is given by: $b_6 - b_7 + b_8 - b_9$