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Research Note

Using Expectation Disconfirmation Theory and Polynomial Modeling to Understand Trust in Technology

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rust in technology is an emerging research domain that examines trust in the technology artifact instead of L trust in people. Although previous research finds that trust in technology can predict important outcomes, little research has examined the effect of unmet trust in technology expectations on trusting intentions. Furthermore, both trust and expectation disconfirmation theories suggest that trust disconfirmation effects may be more complex than the linear expectation disconfirmation model depicts. However, this complexity may only exist under certain contextual conditions. The current study contributes to this literature by introducing a nonlinear expectation disconfirmation theory model that extends understanding of trust-in-technology expectations and disconfirmation. Not only does the model include both technology trust expectations and technology trusting intention, it also introduces the concept of expectation maturity as a contextual factor. We collected data from three technology usage contexts that differ in expectation maturity, which we operationalize as length of the introductory period. We find that the situation, in terms of expectation maturity, consistently matters. Using polynomial regression and response surface analyses, we find that in contexts with a longer introductory period (i.e., higher expectation maturity), disconfirmation has a nonlinear relationship with trusting intention. When the introductory period is shorter (i.e., expectation maturity is lower), disconfirmation has a linear relationship with trusting intention. This unique set of empirical findings shows when it is valuable to use nonlinear modeling for understanding technology trust disconfirmation. We conclude with implications for future research.

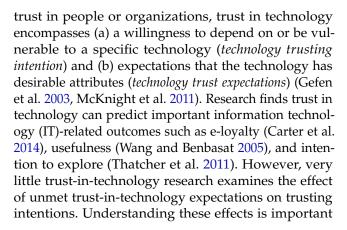
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1. Introduction

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The trust literature explains that trust can be strengthened when expectations are met and harmed when expectations are violated (Lewicki et al. 2006, Robinson 1996). However, little research has examined how this works, especially regarding trust in technology. *Trust in technology* refers to trust in the technology artifact itself, such as online recommendation agents (Wang and Benbasat 2005) and knowledge management systems (Thatcher et al. 2011). Trust in technology for an outcome, and the possibility exists that the technology may not enable that outcome. Similar to



because unmet expectations can negatively influence IT usage, which could undermine organizations' attempts to exploit IT (Bhattacherjee and Premkumar 2004).

Recognizing its importance, Venkatesh et al. (2011) use an expectation disconfirmation theory (EDT) model (Bhattacherjee and Premkumar 2004) to study technology trust expectations. IT EDT research shows that people develop satisfaction by first developing initial expectations while starting to use the technology, and then by comparing technology performance during a subsequent usage period against initial expectations (Bhattacherjee and Premkumar 2004). Using EDT to study trust in technology is reasonable because the trust literature describes how people build trust by confirming or disconfirming prior expectations (Kim and Tadisina 2007, Lewicki et al. 2006, Rousseau et al. 1998). EDT provides a theoretical basis for understanding expectations and disconfirmation (i.e., unmet expectations).

Whereas a linear EDT model reveals an important cognitive chain of events, other theories suggest disconfirmation may have nonlinear effects. Cognitive dissonance theory posits that disconfirmation may not be linear because any discrepancy—positive or negative—can negatively impact outcomes (Festinger 1957). Also, prospect theory, which contends that people focus on losses more than gains (Kahneman and Tversky 1979), implies differential effects of positive and negative disconfirmation on outcomes. Venkatesh and Goyal (2010) find support for these theories using polynomial models of IT usefulness and attitude disconfirmation. Their nonlinear findings suggest researchers should reconsider previous linear results and investigate when nonlinear models are more appropriate.

Trust theory also suggests trust disconfirmation effects may be nonlinear (Adobor 2005, Gambetta 2000, Jarvenpaa et al. 2004, Lewicki and Bunker 1995, McEvily et al. 2003, Robinson et al. 2004), with similar effects as those proposed by cognitive dissonance and prospect theory. However, trust's effects may be contextor situation-dependent (Jarvenpaa et al. 2004),¹ as demonstrated by mixed research findings. For example, Venkatesh and Goyal (2010) find polynomial effects for usefulness disconfirmation, but Brown et al. (2008) do not. Researchers acknowledge an infinite number of situational features exist among contexts, and urge scholars to ground context-related choices in theory (Bamberger 2008, Hong et al. 2014). Although many situational factors could explain these differences, Oliver (1976) claims and finds that nonlinear effects are more likely when subjects have what he calls "stronger" or more confident initial expectations. We address this by proposing that nonlinear effects of technology trust

disconfirmation may exist only when initial expectations are more mature. We define "more mature" as being based on more first-hand experience with the technology than reputational information or first impressions. Information and experience make mature expectations more confident, solid, and firm (McKnight et al. 2004). Thus, expectation maturity may influence when nonlinear effects of trust disconfirmation will occur.

Overall, our research objective is to better understand trust in technology's nonlinear nature from an expectation disconfirmation perspective. Our first potential contribution is to better understand when nonlinear effects might occur. We do so by examining three different IT contexts: graduate student use of Webdevelopment software (Joomla!), undergraduate student use of presentation software (Prezi), and employee use of customer relationship software (Salesforce.com; SF). We argue that initial expectations will differ in maturity among the contexts based on the length of the introductory periods. These expectation maturity differences will produce varying polynomial results. We find support for our hypotheses, suggesting that situational factors are important in studying trust disconfirmation.

Our second potential contribution is in applying Venkatesh and Goyal's (2010) EDT polynomial model to technology trust. Based on trust theory, EDT, and polynomial modeling, our model focuses on how initial technology trust expectations and modified technology beliefs affect technology trusting intention. We also conceptualize technology expectations and modified beliefs with three technology-related trust attributes. We present unique empirical findings using polynomial modeling and response surface techniques. This is a nontrivial advancement to research because it applies theory to fill a gap at the intersection of EDT, trust in technology, and polynomial modeling.

2. A Nonlinear Expectation Disconfirmation Process: Research Model and Hypotheses

EDT researchers find nonlinear effects that coincide with both cognitive dissonance and prospect theories (Anderson and Sullivan 1993, Brown et al. 2012, Cheung and Lee 2009, Lankton and McKnight 2012, Venkatesh and Goyal 2010; for a literature review, see Online Appendix A (available as supplemental material at http://dx.doi.org/10.1287/isre.2015.0611)). Some researchers have also used polynomial modeling and response surface analysis to better understand these expectation disconfirmation nonlinear effects (Brown et al. 2008, 2012; Venkatesh and Goyal 2010). This approach models the expectation disconfirmation process with the regression equation

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

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¹We use the terms "context" and "situation" and "contextual" and "situational" interchangeably.

where *X* equals postusage or modified beliefs, *Y* is preusage beliefs, and *Z* is outcomes.

Polynomial modeling may be especially important for trust because the extent literature has posited nonlinear effects. For example, Jarvenpaa et al. (2004, p. 262) find trust effects are "not necessarily direct and linear."

Our research model combines EDT, trust theory, and polynomial modeling. It examines the polynomial regression model in Equation (1), where X equals postusage modified technology trust beliefs, Y equals preusage technology trust expectations, and Z equals trusting intention. We posit that people have an overall technology trusting expectation that is composed of separate, yet related, expectations about the software's functionality, reliability, and helpfulness (McKnight et al. 2011, Thatcher et al. 2011). Online Appendix B grounds these technology trust dimensions in the trust literature and justifies and defines them. As prescribed for EDT studies (Bhattacherjee and Premkumar 2004), we use the same three attributes for modified technology trust beliefs, which represent one's beliefs about these attributes after using the technology.

Our model also incorporates technology trusting intention as the dependent variable (Equation (1)). Whereas trust beliefs are considered trust's cognitive component, trusting intention indicates a willingness and commitment to depend on the trustee (Benamati et al. 2010). With trusting intention, one makes a conscious choice to put aside doubts and move forward with the relationship (Holmes 1991). Being willing to depend on the trustee (i.e., the technology) means one has a volitional preparedness to make oneself vulnerable and engage in trusting behaviors (i.e., continued system use; Mayer et al. 1995). We include trusting intention in our research model to better reflect the nomological relationship between the cognitive and behavioral trust components. That technology trust beliefs influence trusting intention is a basic tenet of both trust theory (Mayer et al. 1995) and the theory of reasoned action.

2.1. Hypotheses Development

We use EDT, trust theory, cognitive dissonance theory, and prospect theory to guide the hypotheses development (summarized in Online Appendix C). EDT is the underlying theory. It proposes that as disconfirmation becomes more negative, trusting intention decreases (H1A and H1B), and as disconfirmation becomes more positive, trusting intention increases (H2B). We use cognitive dissonance theory, prospect theory, and some additional EDT propositions to support trust's nonlinear effects including the negative effects of positive disconfirmation (H2A), asymmetry between negative and positive disconfirmation effects (H3A and H3B), and disconfirmation's increasing effects (H4). We also use EDT research to support differences based on



expectation maturity (H2A and H2B). Most importantly, because trust is this paper's focus, we discuss how trust theory supports each hypothesis.

EDT's basic premise is that individuals form initial expectations of performance, and after experience, they compare perceived performance with these expectations. This comparison is known as disconfirmation. EDT predicts that as disconfirmation becomes more positive (i.e., performance is better than expected), individuals will feel more pleasure, and outcomes like satisfaction and intention will increase. Also, as disconfirmation becomes more negative (i.e., performance is worse than expected), individuals will feel bad, and these outcomes will decrease (Oliver 1980, Spreng and Page 2003). IT EDT research shows general support for this linear relationship (e.g., Bhattacherjee and Premkumar 2004). However, polynomial EDT research challenges this linear-based assumption. Because polynomial modeling separates disconfirmation into its theoretical components-expectations and performance (i.e., modified beliefs)—we can test hypotheses about differential and curvilinear effects.

To do so, we use the maturity of initial technology trust expectations to differentiate how disconfirmation will affect trusting intention. We define more mature initial expectations as initial expectations that are formed based on more experience with the trustee, and as such feel more confident and firm. This is consistent with trust research that describes two stages of initial trust expectations, introductory and exploratory (McKnight et al. 2004). In the introductory stage, initial trust expectations are formed based on little or no credible, first-hand information about the trustee—only secondhand information about the trustee's reputation. Once the trustor begins interacting with the trustee and gains some credible, first-hand information about the trustee, more confident or experiential expectations can be formed. These expectations are more mature than those in the introductory stage because they are based more on first-hand rather than second-hand impressions (McKnight et al. 2004). People rely more on first-hand experience than second-hand information (Karahanna et al. 1999). Trust researchers also distinguish between fragile and robust trust. Fragile trust expectations are trust beliefs that (a) are formed before the trustor has much experience with the trustee (McKnight et al. 2011), (b) presume that the parties do not yet have credible, meaningful, bonding information about each other (McKnight et al. 1998), and (c) can be inaccurate (Robert et al. 2009). Robust expectations form from repeated transactions so the trustor knows the other party well enough to predict their behavior (Lewicki and Bunker 1995). Trustors have more confidence in these expectations because interpersonal cues from direct experiences are harder to misconstrue (McKnight et al. 1998). Expectations based on experience enable

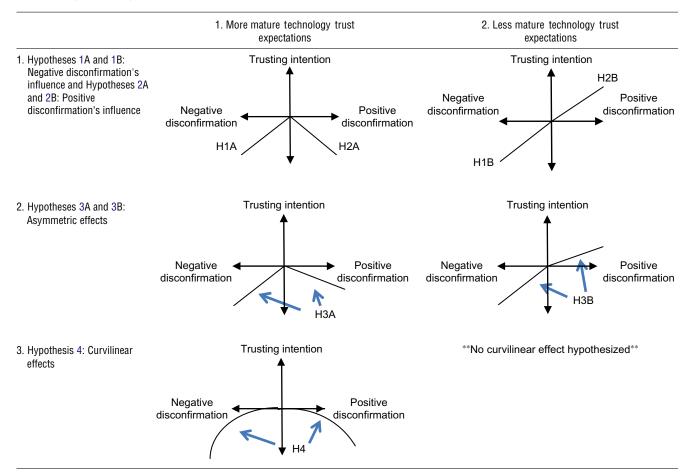
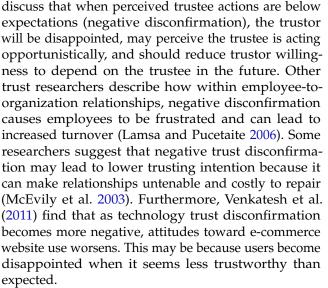


Figure 1 (Color online) Hypotheses Depicted as Two-Dimensional Graphs

one to commit to a trusting relationship (Zhang and Zhang 2005).

Initial expectation maturity has also been identified as a moderating influence on disconfirmation's nonlinear effects (Oliver 1976). Marketing studies show that more mature expectations (referred to by Oliver 1976, p. 247, as "strong expectations," meaning firm or having a basis in something, such as experience) are associated with factors like involvement, commitment, and interest that may increase with experience (Oliver 1976, Terry and Lindsay 1974, Weaver and Brickman 1974). Furthermore, Carlsmith and Aronson (1963) used training to induce more mature expectations in testing disconfirmation's nonlinear effects. Based on this, we consider how the maturity of initial trust expectations will affect the three polynomial hypotheses. Figure 1 depicts these hypotheses in two dimensions, with the x-axis representing disconfirmation and the y-axis representing trusting intention.

2.1.1. Negative Disconfirmation's Influence on Trusting Intention (H1A and H1B; Figure 1, Row 1). Consistent with EDT, trust theory predicts that negative technology trust disconfirmation will have a negative influence on trusting intention. McEvily et al. (2003)



We predict negative disconfirmation will have a negative effect on trusting intention, regardless of the maturity of initial trust expectations (Figure 1, row 1, columns 1 and 2). Lewicki and Bunker (1995) describe how negatively disconfirmed trust expectations lead to lower trusting intentions regardless of the stage of

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trust. Initially, when trust is calculus-based (an early trust form based on comparing costs and benefits of sustaining a relationship versus severing it), negative trust disconfirmation can cause a trustor to end the relationship because in this early stage the trustor will be sensitive and careful about taking relationship risks. In the experiential knowledge-based stage of trust, negative disconfirmation can be unsettling to the trustor, which could destabilize trust. In the identification-based trust stage, negative disconfirmation can disturb underlying values, causing a sense of moral violation from which parties might not recover (Lewicki and Bunker 1995). Hence, we predict negatively disconfirmed trust beliefs make a trustor less willing to depend on the other party, regardless of the maturity of initial expectations.

HYPOTHESIS 1 (H1A). In contexts in which initial technology trust expectations are more mature, negative technology trust disconfirmation will negatively influence trusting intention.

HYPOTHESIS 1 (H1B). In contexts in which initial technology trust expectations are less mature, negative technology trust disconfirmation will negatively influence trusting intention.

2.1.2. Positive Disconfirmation's Influence on Trusting Intention (H2A and H2B; Figure 1, Row 1). Despite EDT's prediction that as disconfirmation becomes more positive it will have positive effects on outcomes, some researchers posit that affective judgments following either positive or negative disconfirmation are an inverse function of the *absolute* degree of perceived disconfirmation (Aronson and Carlsmith 1962, Carlsmith and Aronson 1963, Oliver 1976). In other words, both positive and negative disconfirmation can have negative effects on outcomes. These effects are based on cognitive dissonance theory's tenet that if people firmly expect an event and it does not occur, they will experience dissonance because their expectation that the event will occur is dissonant with the cognition that the event did not occur (Carlsmith and Aronson 1963, Festinger 1957). Any discrepancy will negatively affect outcomes.

The psychological contracts and IT literatures find negative effects of both positive and negative disconfirmation. For example, Lambert et al. (2003) theorize employees who receive less than they expected (i.e., a negative discrepancy) are dissatisfied because of unmet needs. Employees who receive more than they expected (i.e., a positive discrepancy) are dissatisfied because excess levels interfere with need fulfillment. For example, in one study, employees who received less task variety than expected (negative disconfirmation) were dissatisfied because they were bored. Employees who received more task variety than expected (positive disconfirmation) were dissatisfied because it interfered with other responsibilities (Lambert et al. 2003). Venkatesh and Goyal (2010) also find that both positive and negative usefulness and attitude disconfirmation have negative effects on IT continuance intention. They reason that when users have positive disconfirmation, they still might focus on their lower initial expectations, or what the system does not do rather than what it does. This may have negative effects on their usage continuance intentions.

Trust theory predicts that positive disconfirmation may have positive or negative effects on trusting intention. Positive disconfirmation could increase trusting intention because a trustor may want to create equilibrium between expectations and performance by trusting more (McEvily et al. 2003). Researchers discuss how trust builds over time as initial trust expectations are positively disconfirmed, implying that positive disconfirmation increases trusting intention (Lewicki et al. 2006). However, trust theory also predicts negative effects of positive disconfirmation. In regard to positive disconfirmation, there is an opportunity cost to the trustor of unutilized latent trustworthiness. In this situation, a "self-fulfilling prophecy" may occur, causing trust and trust-related behaviors to continue to decrease; that is, if one does not trust another party that is indeed trustworthy, the other party may realize this, and in turn become unmotivated and untrustworthy, causing one's trust in them to decline further and creating a vicious cycle of lower trust and lower trust behaviors (Ghoshal and Moran 1996, McEvily et al. 2003). Positive disconfirmation can also decrease trusting intention because the trustor might believe the trustee is naïve or foolish for trusting so much (i.e., has insufficient sociocultural knowledge and/or believes that people are always motivated to behave responsibly when they are considered capable of responsible acts), which can make the trustor cynical and even less likely to rely on the trustee in the future (Lamsa and Pucetaite 2006). Finally, positive disconfirmation can lead a trustor to be suspicious of the trustee, which can make the trustor more likely to view another's behaviors and motives negatively, despite evidence to the contrary (Gambetta 2000). This can decrease trusting intention.

In marketing, customer satisfaction researchers find that positive disconfirmation has a negative effect when individuals have more mature expectations (Carlsmith and Aronson 1963, Oliver 1976, Terry and Lindsay 1974, Weaver and Brickman 1974). We predict that when technology trust expectations are more mature, positive disconfirmation will have a negative effect on trusting intention (Figure 1, row 1, column 1). Users with mature expectations will feel more dissonance because they had more confidence that their initial prediction was accurate. The discrepancy will seem more stressful,

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and the user may not be as convinced that the higher performance will persist. In a technology trust context, experienced users may find that the technology had more trustworthy attributes than expected (e.g., more functionality than expected), but may still not take advantage of this functionality and depend on the technology for future tasks because they feel bad about being wrong in what they felt was a well-informed prediction. Because, based on first-hand experience, they had more confidence in their technology trust expectations, better than expected performance may make them wary. Based on these theoretical arguments and findings we predict the following:

HYPOTHESIS 2 (H2A). In contexts in which initial technology trust expectations are more mature, positive trust disconfirmation will negatively influence trusting intention.

By contrast, we predict that when initial technology trust expectations are less mature, positive disconfirmation will have a positive effect on trusting intention (Figure 1, row 1, column 2). Individuals will feel less confident in their initial expectations because they were not based on much direct experience (Carlsmith and Aronson 1963, Oliver 1976). As such, users will find the technology's better-than-expected performance as a pleasant surprise, and will not be uncomfortable with the positive technology trust discrepancy (Brown et al. 2008, Oliver 1976). The notion of positive disconfirmation resulting in a pleasant feeling and thereby increasing satisfaction is consistent with contrast theory (Oliver and DeSarbo 1988, Yi 1990). Users will be more likely to focus on the positive experience rather than on their prediction error, making their trusting intention increase. For example, when first being introduced to a technology, users may not comprehend all of its functionality because they lack in-depth experience. Expectations they form about the system's functionality may be lower than warranted. If later experience with the technology shows their initial trust expectations were too low (functionality was greater than expected), this discrepancy will be a pleasant surprise because they know they were not familiar enough with the functionality to predict accurately. In turn, they will be more willing to depend on the higher functioning system.

HYPOTHESIS 2 (H2B). In contexts in which initial technology trust expectations are less mature, positive trust disconfirmation will positively influence trusting intention.

2.1.3. Asymmetric Effects of Positive and Negative Disconfirmation (H3A and H3B; Figure 1, Row 2). We also propose that negative and positive disconfirmation will have asymmetric effects such that negative disconfirmation than will positive disconfirmation. This means one unit of negative disconfirmation will have a greater effect



on the dependent variable than one unit of positive disconfirmation (Lankton and McKnight 2012). Theoretical support for an asymmetric effect comes from research that proposes stronger effects of negative events than positive events. For example, prospect theory claims the disutility caused by losses is greater than the utility caused by equivalent gains (Kahneman and Tversky 1979). Furthermore, the general psychological principle that "bad is stronger than good" posits individuals will react more strongly to bad things as an adaptive response to their environment (Baumeister et al. 2001, p. 323). For example, not reacting to something good may only produce minor regret, whereas not reacting to something bad may have dire consequences (Baumeister et al. 2001). Finally, EDT studies show that disconfirmation has asymmetric relationships with outcomes such that negative disconfirmation has stronger effects on outcomes than does positive disconfirmation (e.g., Anderson and Sullivan 1993, Brown et al. 2012, Lankton and McKnight 2012, Venkatesh and Goyal 2010). They explain that positive disconfirmation may involve some pleasure (Oliver 1980), which can somewhat soften or mitigate its negative dissonance effects. The dissonance or stress caused by getting too much of a good thing is lower than the stress caused by not getting what is expected.

Trust theory supports this asymmetric effect when positive disconfirmation's influence is negative (as in more mature expectation contexts). For example, as we explained in §2.1.1, employees with negative disconfirmation may be frustrated and demoralized, and thus turnover may increase and competitiveness may be lost (Lamsa and Pucetaite 2006). However, employees with positive disconfirmation may think the organization naïve or foolish for trusting too much, and they may form a cynical attitude toward it (Lamsa and Pucetaite 2006). Employees may react negatively because they were confident the organization would not be as trustworthy. Comparatively speaking, the negative effects of negative disconfirmation seem worse than the negative effects of positive disconfirmation. Kim et al. (2004, p. 105) also discuss how negative trust disconfirmation invalidates the "trustworthy until proven otherwise" assumption, causing trust to decrease possibly below the initial trust level. Mistrusted parties must not only reestablish positive expectations but also overcome negative expectations. Also, information about the violation may remain particularly salient, reinforcing negative performance despite efforts by the mistrusted party to demonstrate trustworthiness. These situations suggest that negative disconfirmation effects may be stronger than those of positive disconfirmation.

As argued for H2A above, individuals with more mature initial expectations who have positive technology trust disconfirmation may be guarded and perhaps doubtful that the technology will be as reliable, helpful, or have needed functionality (i.e., be as trustworthy) in the future. This is because they were more confident that their initial expectations were accurate. Although such doubt could cause trusting intention to decrease, there could be some offsetting pleasant feelings or at least some relief that the system is trustworthy enough to complete one's tasks. For this reason, trusting intention will not decrease as much with positive disconfirmation as with negative disconfirmation. If the technology is found to be less trustworthy than expected, the task could be harder to complete. One could be thwarted from completing the task altogether. This type of trust violation could not only make trust decrease, it could very well make one not want to depend on the technology at all. This is a much worse outcome than that for positive disconfirmation.

HYPOTHESIS 3 (H3A). In contexts in which initial technology trust expectations are more mature, the decrease in trusting intention associated with positive disconfirmation will be significantly smaller than the decrease in trusting intention associated with negative disconfirmation.

Support also exists for an asymmetric effect when initial expectations are less mature—i.e., where positive disconfirmation is predicted to have a positive effect on trusting intention (Figure 1, column 2, row 2). For example, early trust theorists describe trusting behavior as a situation in which the disutility one suffers if the other abuses one's vulnerability is perceived as greater than the utility one gains if the other does not abuse that vulnerability (Deutsch 1973, Zand 1972). This implies the downsides (negative disconfirmation) of trust are greater than the upsides (trust confirmation or positive disconfirmation). Also, trust researchers discuss how the buildup of trust from positive disconfirmation is slower and the decrease in trust from negative disconfirmation is more rapid (e.g., Lewicki and Bunker 1995).

We believe that even in conditions of less mature initial expectations positive disconfirmation will still have smaller absolute effects than negative disconfirmation. Again, this is supported by prospect theory (Kahneman and Tversky 1979) and much subsequent work showing negative reactions are more influential than positive ones (e.g., in movie reviews; Chakravarty et al. 2010). A user with little knowledge about the system will have formed less mature initial expectations, and because of this might be pleasantly surprised that the system has better than expected trustworthiness. Although pleasant, this positive disconfirmation will not evoke as much reaction as negative disconfirmation because some level of trust is needed to depend on the technology to complete a task. If the technology is perceived to be untrustworthy, one may not be able to depend on the system at all. Thus, negative reactions will be more severe. We predict the following:

HYPOTHESIS 3 (H3B). In contexts in which initial technology trust expectations are less mature, the increase in

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trusting intention associated with positive disconfirmation will be significantly smaller than the decrease in trusting intention associated with negative disconfirmation.

2.1.4. Curvilinear Effects (H4; Figure 1, Row 3). We also predict that when initial expectations are more mature, positive and negative trust disconfirmation will have increasingly negative effects on trusting intention, resulting in a curvilinear relationship (Figure 1, row 3, column 1). As disconfirmation increases, there is greater psychological discomfort (dissonance) because the inconsistency among a person's beliefs, attitudes, and/or actions increases, making the negative effects on outcome variables increasingly stronger (Venkatesh and Goyal 2010). This effect is grounded in theory that explains there are increasing levels of "unexpectedness" (Oliver 1989). A normal range exists in which expectations can be exceeded such that the experience is perceived to be gratifying or disappointing, but not surprisingly so. Outside the normal range, the level of performance is surprisingly positive or negative (Oliver 1989, 1997). Surprises almost always evoke emotional responses (Berscheid 1983), and the more surprising, the more evocative. This suggests that disconfirmation can have increasing effects on outcomes. The zone of tolerance from service quality research also supports increasing sensitivity, as it proposes relatively flat satisfaction for certain service performance with sharp increases (decreases) for very high (low) performance (Kettinger and Lee 2005, Mittal et al. 1998). The deleterious effects of increasing positive and negative disconfirmation on outcomes have been demonstrated in other contexts (e.g., Hornstein and Houston 1976, Lambert et al. 2003, Venkatesh and Goyal 2010). To our knowledge, it has not been shown for technology trust disconfirmation.

Trust theory suggests that the negative effects of technology trust disconfirmation will show increasing sensitivity on trusting intention. Robinson et al. (2004) explain that the greater the discrepancy or contrast between initial trust and less-than-trustworthy performance by an organization, the more taken advantage of and exploited an employee will feel. The employee will in turn act with much stronger negative emotions of hurt or anger. They may also remember the disconfirmation longer. The impact of a trust violation will be less severe and may not evoke the emotions that a larger discrepancy would with lower initial trust (less discrepancy) (Robinson et al. 2004). Also, trust researchers find that as positive trust-like attributes increase, trust decreases at an increasing or more rapid rate, possibly because the trustor becomes increasingly suspicious of the other's motives, and perceives the trustee's actions as being too unrealistic (Vlachos et al. 2011).

We predict that the increasing effect of positive and negative disconfirmation will occur when initial expectations are more mature because the disappointment or discrepancy will be more emotional. Individuals with stronger initial expectations have more confidence in their expectations and will be especially surprised and dismayed when disconfirmation occurs. Users will become increasingly sensitive to the cognitive dissonance felt when technology trust performance exceeds or falls below initial expectations. For example, users' feelings of anger and hurt may become increasingly stronger if the technology does not live up to its expected trustworthiness. Likewise, as positive disconfirmation increases, one's perception that the technology's trustworthiness is surprisingly better than expected may cause increasingly high suspicion and wariness because it will seem "too good to be true." Also, excess technology trustworthiness could also impose increasingly greater user stress. These conditions will cause negative/positive technology trust disconfirmation to have increasingly stronger negative effects on trusting intention.

HYPOTHESIS 4 (H4). In contexts in which initial expectations are more mature, trusting intention will decrease at a faster rate as negative and positive technology trust disconfirmation increase.

We do not propose a hypothesis for curvilinear effects for contexts in which initial technology trust expectations are less mature (Figure 1, row 3, column 2). The theoretical foundation is not strong enough to posit specific hypotheses—for example, whether positive disconfirmation will increase or decrease at an increasing rate or remain linear. Although we do not develop a specific hypothesis, we test for curvilinearities in this context, which in turn can provide opportunities for future research to theorize and more rigorously test the relationship (Agustin and Singh 2005).

3. Methodology

We test the research model using data from three usage contexts, each over two time periods. One context involves MBA students using Web development software (Joomla!). Another involves undergraduate students using an online presentation solution (Prezi). The other involves organizational employees using a new customer relationship management system (Salesforce.com). All three technologies are cloud based and are accessed primarily through a Web browser. We selected the three contexts based on theoretical sampling (Strauss and Corbin 1990) and case replication sampling (Yin 1989). Although the cases do not answer everything about our research questions, they provide a good start by allowing contrasts between the settings that enable us to test our situational theory and also to eliminate one plausible alternative to our findings.

Theoretical sampling is selection "on the basis of concepts that have proven theoretical relevance to the evolving theory" (Strauss and Corbin 1990, p. 176). We use the part of Strauss and Corbin's (1990) method



about selecting contrasting cases to test theory about their differences. We select SF as a mature expectation case based on the longer introductory period, and by contrast we select Prezi and Joomla! as less mature expectation cases based on the shorter introductory periods. Presurvey introductions to the focal technology are common practice in prior IT EDT research (Bhattacherjee and Premkumar 2004). Longer introductions can give respondents more experience and information to enable them to form better-informed, more confident first-hand impressions of the technology. SF respondents had a three-month introductory period in which users participated in multiple online webinars, Joomla! had a 50-minute (one class session) introduction, and Prezi respondents had a 20-minute online introduction. Although comprehensive software like SF would naturally require a longer introduction, the considerably different introductory time periods could result in SF respondents feeling they have more experience with the technology, and hence have more confident and mature initial technology trust expectations. To validate that SF respondents had more experience than the Prezi and Joomla! respondents, we asked respondents about their experience after the introductory period at the time expectations were measured.

We also select both Prezi and Joomla! as less mature expectation cases for replication purposes. Yin (1989, p. 53) suggests multiple cases be selected to replicate tests when one is expecting the same results from both cases, strengthening a test. Even though the Prezi and Joomla! contexts differ, we expect the same results based on our maturity context theory because they have similar, short introductory periods compared to SF.

Trust is important in all three contexts because the applications are cloud based, creating environmental uncertainties (e.g., poor Internet connections, unavailability, information privacy issues). The technologies can be unreliable, unhelpful, or have less than needed functionality, which can cause employees to feel unproductive and students to feel vulnerable because of grade or class risk. In fact, during the Prezi data collection, the system was down for a while, which caused student anxiety about their assignment. Furthermore, low reliability, functionality, and helpfulness for SF could cause economic losses. The employees and students deal with these uncertainties and risks as they trust and use the technology.

In each study, we administered two questionnaires, three weeks apart. Online Appendix D describes the procedures, the questionnaire items, and the validity tests for the maturity contexts.

4. Data Analysis and Results

We followed the between-group SEM (structural equation modeling) analysis guidelines of Qureshi and Compeau (2009) to choose the appropriate testing

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technique. Because we were looking for medium effect sizes based on our power analysis and had complex arrangements of second-order factors, we used the PLS (partial least squares)-based SEM product XLStat (versions 2012.1 and 2014). XLStat can handle complex SEM-PLS models and polynomial regressions. It also uses current methods to perform group analyses and permutation tests (Chin and Dibbern 2010).

We first analyzed the measurement models for each data set. All measurement model results showed adequate construct validity, as reported in Online Appendix E. Next we analyzed how many respondents had a discrepancy (positive or negative disconfirmation) between expectations and modified technology trust beliefs. We standardized the scores for each variable and counted a standardized score on each variable that is half a standard deviation above or below the standardized score on the variable as having a discrepancy (Fleenor et al. 1996). Over half of the sample in all three usage contexts has a discrepancy (Online Appendix F, Table 1). This verifies the practicality of exploring the discrepancies (Shanock et al. 2010).

Next, we used polynomial modeling and response surface analysis to investigate whether technology trust beliefs have nonlinear effects on trusting intentions. We followed the procedure of Edwards (2002) and Venkatesh and Goyal (2010). First, we ran exploratory, unconstrained linear regression equations with the preusage and postusage variables, as independent variables and technology trusting intention as the dependent variable. In all three linear regressions, the postusage modified technology trust beliefs (*TTMB*₂) significantly explain trusting intention (all p < 0.001), whereas the preusage technology trust expectations (*TTE*₁) have no effect (all p > 0.05; Online Appendix F, Table 2).

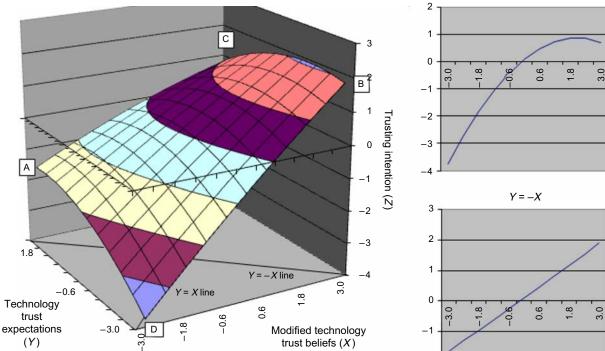
Then we ran exploratory, polynomial models with the pre- and postusage variables and the quadratic and interaction terms (Online Appendix F, Table 2). The postusage modified technology trust belief effects remain significant at p < 0.001 in all three models. Also, we find a significant coefficient for the preusage technology trust expectation-squared term ($\beta = -0.08$, p < 0.05) in the Prezi model. We find a significant coefficient for the postusage modified technology trust belief-squared term ($\beta = -0.16$, p < 0.01) and for the interaction term ($\beta = 0.31$, p < 0.001) in the SF model. Our *F*-tests show that the variances explained (R^2 s) of all three polynomial models are significantly higher (p < 0.001) than the variances explained of the linear models, rejecting the linear models in favor of the three polynomial models (Edwards 1994, 2002; Edwards and Parry 1993).

Finally, we plotted the response surfaces for the polynomial models to interpret the results (Figures 2–4). Response surface graphs are created using the coefficients from the polynomial equations. Each graph has

Y = X

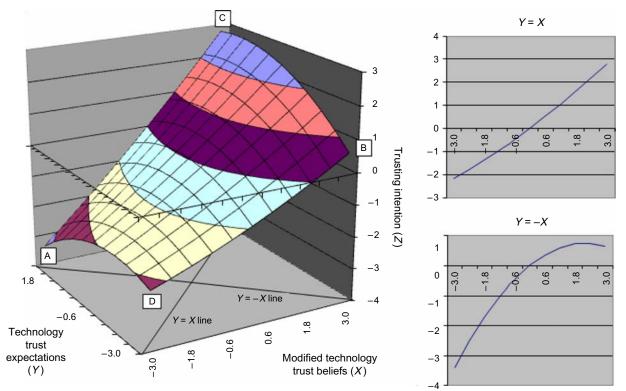
Figure 2 (Color online) Joomla!: Technology Trust—Trusting Intention





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Figure 3 (Color online) Prezi: Technology Trust—Trusting Intention



Note. A, End point of negative disconfirmation; B, end point of positive disconfirmation; C, end point of positive confirmation; D, end point of negative confirmation.

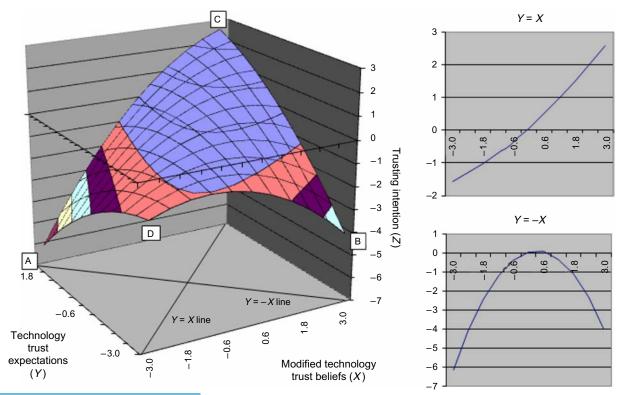


Figure 4 (Color online) Salesforce.com: Technology Trust—Trusting Intention

Note. A, End point of negative disconfirmation; B, end point of positive disconfirmation; C, end point of positive confirmation; D, end point of negative confirmation.



Table 1 Hypothesis Test Results

More mature expectations			Less mature expectations				
Hypotheses	SF results	Supported yes/no	Hypotheses	Joomla! results	Supported yes/no	Prezi results	Supported yes/no
H1A and H2A Test: ρ_{21} is significantly different from 0 and not significantly different from -1	$p_{21} = -0.80^{**}$	Yes	H1B and H2B Test: a_3 is significant and positive, and a_4 is not significant	$a_3 = 0.593^{***}$ $a_4 = 0.00$, ns	Yes	$a_3 = 0.677^{***}$ $a_4 = -0.15$, ns	Yes
H3a Test: a _{negative} disconfirmation > a _{positive} disconfirmation	Difference $= 0.74^*$	Yes	H3B Test: a _{negative disconfirmation} > a _{positive} disconfirmation	$\begin{array}{l} \text{Difference} = \\ -0.02, \text{ns} \end{array}$	No	Difference = 0.90, ns	No
H4: Test: a_4 is significant and negative	$a_4 = -0.57^{**}$	Yes; curvature found	No hypothesis	<i>a</i> ₄ = 0.00, ns	No curva- ture found	<i>a</i> ₄ = -0.15, ns	No curvature found

Note. Formulas: $p_{21} = (b_5 - b_3 - \operatorname{sqrt}((b_3 - b_5)^2 + b_4^2))/b_4$, the slope of the second principal axis; $a_1 = b_1 + b_2$, the linear slope of the Y = X line; $a_2 = b_3 + b_4 + b_5$, the quadratic slope of the Y = X line; $a_3 = b_1 - b_2$, the linear slope of the Y = -X line; $a_4 = b_3 - b_4 + b_5$, the quadratic slope of the Y = -X line; $a_{negative disconfirmation} = [(b_0 + ((b_1 - b_2) \times (-3)) + ((b_3 - b_4 + b_5) \times (-3^2))) - (b_0 + ((b_1 - b_2) \times (0)) + ((b_3 - b_4 + b_5) \times (0^2)))]/(-3 - 0)$, the linear slope of the negative disconfirmation line; $a_{positive disconfirmation} = [(b_0 + ((b_1 - b_2) \times (0)) + ((b_3 - b_4 + b_5) \times (0^2))) - (b_0 + ((b_1 - b_2) \times (3)) + ((b_3 - b_4 + b_5) \times (3^2)))]/(0 - 3)$, the linear slope of the positive disconfirmation line, where b_1 is the coefficient for modified technology trust beliefs, b_2 is the coefficient for technology trust beliefs squared, b_4 is the coefficient for interaction term, and b_5 is the coefficient for technology trust expectations squared.

*Means significantly different from 0 at p < 0.10; **means significantly different from 0 at p < 0.05; ***means significantly different from 0 at p < 0.01.

three main features: a stationary point (the point where the surface is flat; X_0 , Y_0), two principal axes (axes that describe the orientation of the surface in the *X*, *Y* plane; the first principal axis, $Y = p_{10} + p_{11}X$, and the second principal axis, $Y = p_{20} + p_{21}X$), and the surface's shape along lines in the *X*, *Y* plane (the *Y* = *X* or confirmation line, where the pre- and postexposure beliefs are equal, and the *Y* = -X or disconfirmation line, where preand postusage beliefs are different; see Edwards 1994, 2002; Edwards and Parry 1993 for a full discussion of these features). Together these features help explain the response surface. We present these features in Online Appendix F, Tables 3 and 4.

The hypothesis tests and test results are shown in Table 1. Hypotheses 1A and 2A taken together predict that both positive and negative disconfirmation will have a negative impact on trusting intention for the more mature initial technology trust expectation context (SF). These hypotheses are supported if the second principal axis has a negative slope (Venkatesh and Goyal 2010); i.e., if the slope of the second principal axis (p_{21}) is significantly different from 0 and *not* significantly different for H1A and H2A for SF (Table 1, row 1) because p_{21} is significantly different from -1. In support of SF passing this test, Figure 4 shows that points A and B each have a significant downward slope extending away from the Y = X line.

In a more mature context (SF), H3A predicts negative disconfirmation will have a stronger negative effect on trusting intention when compared to the negative effect that positive disconfirmation will have. Hypothesis 3A is supported (Table 1, row 2) because the absolute value of the linear slope of negative disconfirmation,

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 $|a_{\text{negative disconfirmation}|$ (2.07), is significantly greater (p < 0.05) than the absolute value of the linear slope of positive disconfirmation, $|a_{\text{positive disconfirmation}|$ (1.33) (Brown et al. 2012; Table 1). The slope of the negative disconfirmation line is seen in Figure 4 as the line from the response surface midpoint to point A. The slope of the positive disconfirmation line is seen as the response surface midpoint to point B. In support of the hypothesis, Figure 4 shows that trusting intention is lower in the graph's left corner (point A) than in the right corner (point B), indicating negative disconfirmation has a steeper slope than positive disconfirmation.

Finally, H4 is supported if a_4 (the quadratic slope or curvature of the Y = -X line) is significant and negative for the more mature expectation context (SF) (Shanock et al. 2010, Venkatesh and Goyal 2010). We find support for H4 for SF (Table 1, row 3), in that $a_4 = -0.57$ (p < 0.05). For SF trusting intention (Figure 4), this means not only is there a downward sloping surface along the disconfirmation axis (i.e., the surface slopes downward on either side of the Y = X line), per H1A and H2A, but also (per H4) that trusting intention decreases more sharply as the degree of discrepancy increases for both positive and negative technology trust disconfirmation—i.e., as the Y = -Xline approaches points A and B.

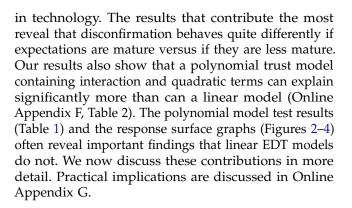
For the less mature initial technology trust expectation contexts (Joomla! and Prezi), H1B and H2B predict that negative disconfirmation will have a negative effect on trusting intention, whereas positive disconfirmation will have a positive effect. Taken together, these hypotheses predict that as disconfirmation becomes more positive, trusting intention will increase. These hypotheses are supported if the linear slope of the Y = -X line (a_3) is significant and positive and the quadratic slope of the $Y = -X(a_4)$ line is not significant. The results for both Joomla! $(a_3 = 0.59, p < 0.01; a_4 = 0.00, ns)$ and Prezi $(a_3 = 0.67, p < 0.01; a_4 = -0.15, ns)$ support these hypotheses (Table 1, row 1, "less mature" columns). Negative disconfirmation has a negative effect on trusting intention, and positive disconfirmation has a positive effect. As further evidence for this effect, for Joomla!, $p_{21} = 1.670$, and for Prezi, $p_{21} = -2.529$, which are both significantly different from 0 and -1. This means a nonlinear effect is not supported.

Again for the less mature technology contexts (Joomla! and Prezi), H3B predicts that negative technology trust disconfirmation will have a stronger negative effect on trusting intention compared to the positive effect that positive disconfirmation will have. Similar to H3A, this hypothesis is also supported if the absolute value of $a_{\text{negative disconfirmation}}$ is significantly greater than the absolute value of $a_{\text{positive disconfirmation}}$ (Brown et al. 2012). We find that H3B is not supported because neither Joomla! (-0.02, ns) nor Prezi (0.90, ns) shows a significant difference between these linear slopes for negative and positive disconfirmation (Table 1). Figures 2 and 3 show this visually. The slopes going up from the response surface midpoint to point B are not significantly less than those going down from the midpoint to point A.

Although we did not hypothesize any curved disconfirmation (Y = -X) line for less mature contexts, Table 1, row 3, reports results that correspond to H4. The a_4 quadratic slope or curvature of the Y = -X line is not significant for either Joomla! or Prezi, which shows there is no support for curved disconfirmation for the less mature context.

5. Discussion, Implications, Limitations, and Future Research Directions

This research uses EDT, polynomial modeling, and trust theory to examine unmet trust-in-technology expectations. This Research Note makes two primary contributions that relate to the theoretical contribution types Whetten (2009) outlines. First, we contribute to theory, which includes formulating new theory and improving existing theory (Hong et al. 2014, Whetten 2009). We refine theory relating to EDT polynomial models and trust by theorizing that the effects of trustin-technology disconfirmation on trusting intention depend on expectation maturity. Second, a contribution of theory uses a theory that has been broadly accepted in the field of study but that has not been applied to the targeted phenomenon (Hong et al. 2014, Whetten 2009). We make a contribution of theory by using EDT, a broadly accepted theory, and polynomial modeling to examine a less studied domain: trust



5.1. Contribution 1. Contribution to Theory: Expectation Maturity Makes a Difference

Maturity is a situational factor, which Jarvenpaa et al. (2004) encourage trust researchers to examine. Our maturity-related hypotheses were mainly based on Oliver's (1976) early EDT work and the trust literature. The only other research to our knowledge to have theorized mature expectations is early marketing research that, for example, examines expectations of a recently introduced automobile (Oliver 1976) and bitter and sweet solutions (Carlsmith and Aronson 1963). Our theory extends this early work. Whereas Oliver (1976) theorizes and manipulates involvement, commitment, and interest as indicators of maturity, we theorize as a maturity indicator that the length of the software introduction period itself matters. Although it is likely that over a longer introduction period users will develop higher involvement, commitment, and interest, we studied at the more general level of analysis, involving the passage of time. Also, whereas Oliver (1976) uses hedonic affective reactions as the dependent variable, we use trusting intention. Using the trust literature to support these hypotheses was important because our dependent variable and its predictor variables are all trust concepts. Trust theorizing has become a significant area of IT study, though little work has examined how trust works in an expectation disconfirmation context. We extend theory by adding expectation maturity as a contextual factor that can determine how trusting disconfirmation affects trusting intention.

5.1.1. Empirical Findings. Related to Contribution 1 (to theory), we find empirically that expectation maturity matters consistently across the hypothesis tests. First, when expectations are more mature (with SF; H1A, H2A; Table 2, row 1), both negative disconfirmation and positive disconfirmation negatively influence trusting intention. This indicates that both positive and negative disconfirmation create negative dissonance, since solid, well-formed expectations are violated. By contrast, when expectations are less mature (with Joomla! and Prezi; H1B, H2B), negative disconfirmation again negatively influences trusting intention, whereas positive disconfirmation positively influences

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	Less mature	More mature expectations	
	Joomla!	Prezi	SF
A. Model results			
H1A, H1B, H2A, and H2B	Only negative disconfirmation decreases trusting intention	Only negative disconfirmation decreases trusting intention	Both negative and positive dis confirmation decrease trust ing intention
H3A and H3B	No asymmetry	No asymmetry	Asymmetry
H4	No curvilinear results	No curvilinear results	Curvilinear results
3. Contextual factors			
Time 2 survey given	3 weeks postintroduction	3 weeks postintroduction	3 weeks postintroduction
Introductory period (time period before expectation assessed) maturity details	1 50-minute class	1 20-minute tutorial	3 months
Experience reported at T1 (1 = no experience to 7 = extensive experience)	Level of experience with Joomla! was 1.30	Level of experience with Prezi was 1.50	Level of experience with SF was 2.81
Change in experience level reported (effect size from Time 1 to Time 2)	Large effect size (0.66)	Large effect size (0.57)	Small effect size (0.24)
Software complexity level (T2	High	Medium	Medium
perceived ease of use reversed —1 to 7 scale)	Mean ease of use, 4.42	Mean ease of use, 3.56	Mean ease of use, 3.37
Classroom versus work context	Classroom–MBA	Classroom–Undergrad	Work

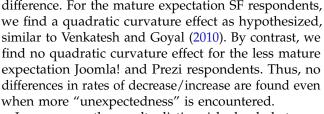
Table 2 Model Results and Contextual Factors by Technology Context

trusting intention. Positively disconfirming the expectation creates a pleasant surprise that overcomes the dissonant feelings, which is probably natural when expectations are not solidly formed. It is hard to feel slighted or piqued at positive disconfirmation when the original expectations were based on brief initial experience with the technology. Cognitive dissonance theory is not supported in this context. Rather, the unexpectedly favorable results overcome any negative feelings.

Second, as expected with more mature expectations, the decrease in trusting intention associated with positive disconfirmation is smaller than the decrease associated with negative disconfirmation, and is thus asymmetric (Table 2, row 2; H3A). By contrast, and contrary to our predictions, with less mature expectations (H3B), we find that the increase in positive disconfirmation-related trusting intention is not smaller than the decrease in negative disconfirmation-related trusting intention, and thus not asymmetric. Maturity again makes a difference. Although prospect theory and the "bad is stronger than good" principle predict that individuals will react to negative situations more than positive situations, our results suggest that the low initial expectation maturity tempers these effects (Table 2).

Third, we find a difference between more mature and less mature contexts in the quadratic curvature of the Y = -X line (Table 2, row 3; H4). We proposed that in mature contexts, we would find a quadratic curvature. We did not feel justified proposing the shape in the less mature context. However, the results show a clear

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In summary, the results distinguish clearly between the mature and less mature expectation contexts (top half of Table 2). Disconfirmation has a strictly linear relationship with trusting intention for less mature expectation contexts, and an asymmetrical, concave shape for more mature expectation contexts. These consistent distinctions between mature and less mature expectations provide initial evidence that expectation maturity affects the quadratic EDT relationships. It puts theoretical boundaries on polynomial relationships, and opens numerous opportunities for future research to explore context effects. For example, the mixed findings of Venkatesh and Goyal (2010) and Brown et al. (2008) regarding usefulness disconfirmation could be due to expectation maturity or other situational factors related to usefulness that have not yet been examined.

5.1.2. Situational Context Becomes Important for Studying Trust. This paper answers calls to study trust within contexts (Jarvenpaa et al. 2004). Similarities and differences exist among our three contexts (bottom half of Table 2). One similarity is that all three studies had a three-week time period between the Time 1 and Time 2 measurements (first "Contextual factors" row in Table 2). The next row details the maturity differences

showing that both Prezi and Joomla! respondents had a relatively short introductory period, whereas the SF respondents had three months. The next Table 2 row also indicates this difference. At Time 1 (the end of the introductory period), the SF respondents felt they had had more experience (2.8 on a seven-point scale) than did the Prezi or Joomla! respondents (1.5 and 1.3 on the seven-point scale, respectively; both p < 0.01). The next row shows the SF respondents reported a lower change in experience during the three-week usage period than did the others, indicating that more of their total experience was gained before the threeweek period. Running a repeated measures analysis of variance (ANOVA) in SPSS 21.0, we find that the effect sizes for the change in experience were 0.66 for Joomla!, 0.57 for Prezi, and 0.24 for SF. Using Cohen's basic guidelines, the effect sizes for three weeks of experience for Joomla! and Prezi were large (r > 0.50), whereas the effect size for SF was small (0.10 < r < 0.30).

5.1.3. Eliminating One Alternative Hypothesis. It is possible that alternative reasons exist for our results. Researchers should try to eliminate plausible alternative reasons to provide greater assurance that their results are not only a good theory but also the best theory for a phenomenon (Cook and Campbell 1979, Stinchcombe 1968). Using two tests is more convincing than using a single test (Stinchcombe 1968, Yin 1989). We do this by testing our theory using two less mature samples (Prezi and Joomla!) and finding consistent agreement between them (Table 1). However, Stinchcombe (1968, p. 25) discusses a more convincing test. He says a researcher can use a "crucial experiment" to set up a plausible alternative theory that, if supported, would show the cause of the phenomenon is different from what the researcher proposes.

The second to last row in Table 2 shows our analysis used to eliminate a plausible alternative to our results. One possible reason for our result differences could be technology complexity.² SF might be perceived as more complex because it is a software suite of products rather than software like Prezi, a presentation solution, and Joomla!, a content management system, which are more specific to a particular task. Complexity could make meeting one's expectations more crucial, making either positive or negative disconfirmation harmful. Thus, a plausible alternative hypothesis (H_a) is that perceived software complexity affects the polynomial relationships just as expectation maturity does.

Since we did not measure perceived complexity, we were not able to test H_a directly. However, we did measure perceived ease of use, which can be used (reverse scored) as a surrogate for system complexity (Moore and Benbasat 1991). The second to last row in

² We credit one of our helpful reviewers for this idea.



Table 2 reports complexity measured as perceived ease of use. We find that Prezi and SF have significantly lower perceived complexity (3.56 and 3.37, respectively) than Joomla! (4.42). Prezi and SF complexities are not significantly different from each other. Given this result, for H_a we would expect to see that both positive and negative disconfirmation for Joomla! would have negative effects on trusting intention, and for SF and Prezi only negative disconfirmation would have a negative effect, while positive disconfirmation would have a positive effect. We find H_a is contradicted by our actual results (for H1A, H1B, H2A, H2B; Table 2, row 1). Both positive and negative disconfirmation for SF have negative effects on trusting intention, and only negative disconfirmation has negative effects for both Joomla! and Prezi. Since H_a is not supported, these results eliminate software complexity as a plausible alternative

5.2. Contribution 2. Contribution of Theory: Applying EDT to Polynomial Models for Trust in Technology

This study fills a research gap where EDT, polynomial modeling, and trust in technology intersect. This gap is important to pursue because whereas EDT research is very large, the other two research domains are small. Whereas trust in people, organizations, and Internet vendors are all becoming large research domains, trust in specific technologies is still very small. This is partly because early influential researchers argued that people trust people, not technologies (e.g., Friedman et al. 2000); that is, human trust in humans is natural because humans can be judged for their moral traits of trustworthiness, such as benevolence and integrity, whereas technologies cannot. In this paper, we argue that trust in a technology is based on what the technology can do for the person, such as giving help and being reliable (Online Appendix B). This allows trust in technology to be researched without making unwarranted assumptions about what a technology can do.

The polynomial modeling literature in IT is also quite small, but is growing. This is one of the few papers that have studied both trusting beliefs and trusting intention (e.g., Benamati et al. 2010), but even fewer that have studied these two constructs using polynomial models. Trust research needs this kind of analysis, because it is not yet clear how linear or nonlinear trust relationships are. This is because few have studied the boundaries of trust in an IT setting (for an exception, see Gefen and Pavlou 2011). Proposing that trust is nonlinear enhances our understanding of how it operates. Predicting the polynomial effects, we also tied into the IT EDT literature (e.g., Venkatesh and Goyal 2010), which is supported by cognitive dissonance and prospect theory. Applying EDT and polynomial modeling concepts to trust in technology also contributes.

In addition, our results contribute to the literature examining a linear technology trust-building process (Venkatesh et al. 2011). We test a linear EDT model (Online Appendix H) and find that expectations and modified technology trust beliefs do not always influence postusage variables. To better compare with the nonlinear results, we also examine the linear effects of disconfirmation on trusting intention. For all three usage contexts, we find the coefficients for the links to trusting intention are not significant. The polynomial model shows that modified technology trust beliefs and expectations, which form disconfirmation, do have important influences on trusting intention. These results point to the advantages of studying the polynomial effects of trust in technology.

5.3. Limitations, Future Research, and Conclusion

Our results are particular to our constructs and the samples we collected, limiting generalizability. For example, Joomla! and Prezi had very short introductory periods, whereas SF had a fairly long period. This means that although we found clear differences, contrasting technologies with other maturity ranges may produce different results. We also studied three specific technologies, which limits how far we can generalize to other technologies. Additionally, we used very specific variables. Studying other variables besides ours will produce different results. Future research can build on this study to address these limitations.

We were not able to eliminate a second plausible alternative, the respondent participation environment context. Both Joomla! and Prezi involved classroom use, whereas the SF context examined work-related use (Table 2, last row). It is possible that this dissimilarity in context made a difference in the results. Future research that selects a less mature group in a work-related use context or a mature group in a classroom environment would constitute another "crucial experiment" that would eliminate this alternative.

Researchers could also test the maturity hypotheses with other independent and dependent variables. For example, although we believe SF respondents may be higher in commitment, involvement, and interest than Joomla! or Prezi respondents, we did not measure these factors. Future research can measure these and other factors that might contribute to more mature initial expectations.

We also used system-like technology trust attributes, not interpersonal trust attributes. The differences between system-like trust beliefs and the interpersonal trust beliefs more commonly examined in the information systems literature may affect the generalizability of our findings to other previously studied contexts. Future research could also use interpersonal trust beliefs to evaluate whether our results are specific to technology trust. Furthermore, the system-like technology trust attributes may have some overlap with



system quality attributes. However, the technology trust attributes are well grounded in trust theory. For example, McKnight (2005) describes trust in technology as having reliability and functionality dimensions (as opposed to integrity and competence ones) because technologies have different capabilities than people. People have volition and moral capability, for example, whereas computers do not. Also, Table 1 in McKnight et al. (2002) shows that the reliability aspect of trust was also used in interpersonal contexts in seven papers published between 1967 and 1996. Similarly, Lippert (2001) uses functionality as early as her 2001 dissertation under the term "system utility." Helpfulness is newer (McKnight et al. 2011), but relates to the computer's capabilities to enact something similar to benevolence in terms of providing responsive help to the user. In summary, these technology trust variables manifest trust theory grounding (see Online Appendix B for details).

Another study limitation is that even though we tested moderation by contrasting the results from mature and less mature samples, we did not test moderation directly using statistical means. This was because we know of no technique for testing moderation with polynomial modeling and a response surface methodology. Neither did we find anyone who had utilized this technique. This represents another future research opportunity.

In conclusion, this paper studies how expectation maturity, a situational context factor, affects trust. We contribute first by theorizing and finding contrasting nonlinear response surface results in mature expectation versus less mature expectation contexts. We also contribute by being among the first to apply EDT and polynomial modeling response surface analysis to technology trust. We feel confident the interesting findings of this study will initiate additional studies on technology trust expectations.

Supplemental Material

Supplemental material to this paper is available at http://dx .doi.org/10.1287/isre.2015.0611.

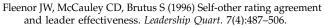
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References

- Adobor H (2005) Trust as sensemaking: The microdynamics of trust in interfirm alliances. J. Bus. Res. 58(3):330–337.
- Agustin C, Singh J (2005) Curvilinear effects of consumer loyalty determinants in relational exchanges. J. Marketing Res. 42(1): 96–108.

- Anderson EW, Sullivan MW (1993) The antecedents and consequences of customer satisfaction for firms. *Marketing Sci.* 12(2):125–143.
- Aronson E, Carlsmith JM (1962) Performance expectancy as a determinant of actual performance. J. Abnormal Soc. Psych. 65(3):178–183.
- Bamberger PA (2008) Beyond contextualization: Using context in theories to narrow the micro-macro gap in management research. *Acad. Management J.* 51(5):839–846.
- Barki H, Harwick J (1994) Measuring user participation, user involvement, and user attitude. MIS Quart. 3(1):59–82.
- Baumeister RF, Bratslavsky E, Finkenauer C, Vohs KD (2001) Bad is stronger than good. *Rev. General Psych.* 5(4):323–370.
- Benamati JS, Fuller MA, Serva MA, Baroudi J (2010) Clarifying the integration of trust and TAM in e-commerce environments: Implications for systems design and management. *IEEE Trans. Engrg. Management* 57(3):380–393.
- Berscheid E (1983) Emotion. Kelley HH, Berscheid E, Christensen A, Harvey JH, Huston TL, Levinger G, McClintock E, Peplau LA, Peterson DR, eds. *Close Relationships* (W. H. Freeman, New York), 110–168.
- Bhattacherjee A, Premkumar G (2004) Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quart.* 28(2):229–254.
- Brown SA, Venkatesh V, Goyal S (2012) Expectation confirmation in technology use. *Inform. Systems Res.* 23(2):474–487.
- Brown SA, Venkatesh V, Kuruzovich J, Massey AP (2008) Expectation confirmation: An examination of three competing models. Organ. Behav. Human Decision Processes 105(1):52–66.
- Carlsmith JM, Aronson E (1963) Some hedonic consequences of the confirmation and disconfirmation of expectancies. J. Abnormal Soc. Psych. 66(2):151–156.
- Carter M, Wright RT, Thatcher JB, Klein RR (2014) Understanding online customers' ties to merchants: The moderating influence of trust on the relationship between switching costs and e-loyalty. *Eur. J. Inform. Systems* 23(1):185–204.
- Chakravarty A, Liu Y, Mazumdar T (2010) The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluation. J. Interactive Marketing 24(3):185–197.
- Cheung CMK, Lee MKO (2009) User satisfaction with an Internetbased portal: An asymmetric and nonlinear approach. J. Amer. Soc. Inform. Sci. Tech. 60(1):111–122.
- Chin WW, Dibbern J (2010) A permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross of information system services between Germany and the USA. Vinzi VE, Chin WW, Henseler J, Wang H, eds. Handbook of Partial Least Squares: Concepts, Methods and Applications in Marketing and Related Fields (Springer-Verlag, Berlin Heidelberg), 171–192.
- Cohen J, Cohen P, West SG, Aiken LA (2003) Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (Lawrence Erlbaum Associates, Mahwah, NJ).
- Cook TD, Campbell DT (1979) *Quasi-Experimentation: Design and Analysis Issues for Field Settings* (Rand McNally, Chicago).
- Deutsch M (1973) The Resolution of Conflict: Constructive and Destructive Processes (Yale University Press, New Haven, CT).
- Edwards JR (1994) The study of congruence in organizational behavior research: Critique and a proposed alternative. *Organ. Behav. Human Decision Processes* 58(1):51–101.
- Edwards JR (2002) Alternatives to difference scores: Polynomial regression analysis and response surface methodology. Drasgow F, Schmidt N, eds. *Measuring and Analyzing Behavior in Organizations: Advances in Measurement and Data Analysis* (Jossey-Bass/Pfeiffer, San Francisco), 350–400.
- Edwards JR, Parry ME (1993) On the use of polynomial regression equations as an alternative to difference scores in organizational research. *Acad. Management J.* 36(6):1577–1613.
- Faul F, Erdfelder E, Lang AG, Buchner A (2007) G*Power3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavioral Res. Methods* 39(2):175–191.
- Festinger L (1957) A Theory of Cognitive Dissonance (Stanford University Press, Stanford, CA).



- Friedman B, Khan PH Jr, Howe DC (2000) Trust online. Comm. ACM 43(12):34-40.
- Gambetta D (2000) Can we trust trust? Gambetta D, ed. Trust: Making and Breaking Cooperative Relations (Basil Blackwell Ltd., Oxford, UK), 213–237.
- Gefen D, Pavlou PA (2011) The boundaries of trust and risk: The quadratic moderating role of institutional structures. *Inform. Systems Res.* 23(3):940–959.
- Gefen D, Karahanna E, Straub DW (2003) Trust and TAM in online shopping: An integrated model. *MIS Quart*. 27(1):51–90.
- Ghoshal S, Moran P (1996) Bad for practice: A critique of transaction cost theory. Acad. Management Rev. 21(1):13–47.
- Holmes JG (1991) Trust and the appraisal process in close relationships. Jones WH, Perlman D, eds. Advances in Personal Relationships, Vol. 2 (Jessica Kingsley, London), 57–104.
- Hong WF, Chan KY, Thong JYL, Chasalow LC, Dhillon G (2014) A framework and guidelines for context-specific theorizing in information systems research. *Inform. Systems Res.* 25(1):111–136.
- Hornstein D, Houston BK (1976) The expectation-reality discrepancy and premature termination from psychotherapy. J. Clinical Psych. 32(2):373–378.
- Jarvenpaa SL, Shaw TR, Staples DS (2004) Toward contextualized theories of trust: The role of trust in global virtual teams. *Inform. Systems Res.* 15(3):250–267.
- Kahneman D, Tversky A (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47(2):263–292.
- Karahanna E, Straub DW, Chervany NL (1999) Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quart.* 23(2):183–207.
- Kettinger WJ, Lee CC (2005) Zones of tolerance: Alternative scales for measuring information systems service quality. *MIS Quart*. 29(4):607–618.
- Kim E, Tadisina S (2007) A model of customers' trust in e-business: Micro-level inter-party trust formation. J. Comput. Inform. Systems 48(1):88–104.
- Kim PH, Cooper CD, Ferrin DL, Dirks KT (2004) Removing the shadow of suspicion: The effects of apology versus denial for repairing competence- versus integrity-based trust violations. *J. Appl. Psych.* 89(1):104–118.
- Lambert LS, Edwards JR, Cable DM (2003) Breach and fulfillment of the psychological contract: A comparison of traditional and expanded views. *Personnel Psych.* 56(4):895–934.
- Lamsa AM, Pucetaite R (2006) Development of organizational trust among employees from a contextual perspective. *Bus. Ethics* 15(2):130–141.
- Lankton NK, McKnight DH (2012) Examining two expectation disconfirmation theory models: Assimilation and asymmetry effects. J. Assoc. Inform. Systems 13(2):88–115.
- Lewicki RJ, Bunker BB (1995) Trust in relationships: A model of trust development and decline. Bunker BB, Rubin JZ, eds. Conflict, Cooperation, and Justice (Jossey-Bass, San Francisco), 133–173.
- Lewicki RJ, Tomlinson ED, Gillespie N (2006) Models of interpersonal trust development: Theoretical approaches, empirical evidence, and future directions. J. Management 32(6):991–1022.
- Lippert SK (2001) An exploratory study into the relevance of trust in the context of information systems technology. Unpublished doctoral dissertation, George Washington University, Washington, DC.
- Mayer RC, Davis JH, Schoorman FD (1995) An integrative model of organizational trust. Acad. Management Rev. 20(3):709–734.
- McEvily B, Perrone V, Zaheer A (2003) Trust as an organizing principle. *Organ. Sci.* 14(1):91–103.
- McKnight DH (2005) Trust in information technology. Davis GB, ed. The Blackwell Encyclopedia of Management: Management Information Systems (Blackwell, Malden, MA), 329–331.
- McKnight DH, Choudhury V, Kacmar C (2002) Developing and validating trust measures for e-commerce: An integrative typology. *Inform. Systems Res.* 13(3):334–359.
- McKnight DH, Cummings LL, Chervany NL (1998) Initial trust formation in new organizational relationships. Acad. Management Rev. 23(3):473–490.

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- McKnight DH, Kacmar C, Choudhury V (2004) Shifting factors and the ineffectiveness of third party assurance seals: A two-stage model of initial trust in a Web business. *Electronic Markets* 14(3):252–266.
- McKnight DH, Carter M, Thatcher JB, Clay PF (2011) Trust in a specific technology: An investigation of its components and measures. ACM Trans. Management Inform. Systems 2(2):1–15.
- Mittal V, Ross WT Jr, Baldasare PM (1998) The asymmetric impact of negative and positive attribute-level performance on overall satisfaction and repurchase intentions. *J. Marketing* 62(1): 33–47.
- Moore GC, Benbasat I (1991) Development of an instrument to measure the perceptions of adopting an information technology innovation. *Inform. Systems Res.* 2(3):192–222.
- Oliver RL (1976) Hedonic reactions to the disconfirmation of product performance expectations: Some moderating conditions. J. Appl. Psych. 61(2):246–250.
- Oliver RL (1980) A cognitive model for the antecedents and consequences of satisfaction. J. Marketing Res. 17(3):460–469.
- Oliver RL (1989) Processing of the satisfaction response in consumption: A suggested framework and research propositions. J. Consumer Satisfaction, Dissatisfaction Complaining Behav. 2:1–6.
- Oliver RL (1997) Satisfaction: A Behavioral Perspective on the Consumer (McGraw-Hill, New York).
- Oliver RL, DeSarbo WS (1988) Response determinants in satisfaction judgments. J. Consumer Res. 14(4):495–507.
- Qureshi I, Compeau D (2009) Assessing between-group differences in information systems research: A comparison of covarianceand component-based SEM. *MIS Quart*. 33(1):197–214.
- Robert LP, Dennis AR, Hung YTC (2009) Individual swift trust and knowledge-based trust in face-to-face and virtual team members. J. Management Inform. Systems 26(2):241–279.
- Robinson S, Dirks K, Ozcelik H (2004) Untangling the knot of trust and betrayal. Kramer RM, Cook KS, eds. *Trust and Distrust in Organizations: Dilemmas and Approaches* (Russell Sage Foundation, New York), 327–341.
- Robinson SL (1996) Trust and breach of the psychological contract. *Admin. Sci. Quart.* 41(4):574–599.
- Rousseau DM, Sitkin SB, Burt RS, Camerer C (1998) Not so different after all: A cross-discipline view of trust. Acad. Management Rev. 23(3):393–404.
- Shanock LR, Baran BE, Gentry WA, Pattison SC (2010) Polynomial regression with response surface analysis: A powerful

approach for examining moderation and overcoming limitations of difference scores. J. Bus. Psych. 25(4):543–554.

- Spreng RA, Page TJ Jr (2003) A test of alternative measures of disconfirmation. Decision Sci. 34(1):31–62.
- Stinchcombe AL (1968) Constructing Social Theories (Harcourt, Brace & World, New York).
- Strauss A, Corbin J (1990) Basics of Qualitative Research (Sage, Newbury Park, CA).
- Terry RL, Lindsay D (1974) Expectancy confirmation and affectivity: A role playing variation. *Psych. Record* 24(4):469–475.
- Thatcher JB, McKnight DH, Baker EW, Arsal RE, Roberts NH (2011) The role of trust in postadoption IT exploration: An empirical examination of knowledge management systems. *IEEE Trans. Engrg. Management* 58(1):56–70.
- Venkatesh V, Goyal S (2010) Expectation disconfirmation and technology adoption: Polynomial modeling and response surface analysis. *MIS Quart.* 34(2):281–303.
- Venkatesh V, Thong JYL, Chan FKY, Hu PJH, Brown SA (2011) Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context. *Inform. Systems J.* 21(6):527–555.
- Vlachos PA, Vrechopoulos AP, Pramatari K (2011) Too much of a good thing: Curvilinear effects in the evaluation of services and the mediating role of trust. *J. Services Marketing* 25(6): 440–450.
- Wang W, Benbasat I (2005) Trust in and adoption of online recommendation agents. J. Assoc. Inform. Systems 6(3):72–101.
- Weaver D, Brickman P (1974) Expectancy, feedback, and disconfirmation as independent factors in outcome satisfaction. J. Personality Soc. Psych. 30(3):420–428.
- Whetten DA (2009) An examination of the interface between context and theory applied to the study of Chinese organizations. *Management Organ. Rev.* 5(1):29–55.
- Yi Y (1990) A critical review of consumer satisfaction. Zeithaml VA, ed. *Review of Marketing* (American Marketing Association, Chicago), 68–123.
- Yin RK (1989) Case Study Research: Design and Methods (Sage, Thousand Oaks, CA).
- Zand DE (1972) Trust and managerial problem solving. *Admin. Sci. Quart.* 17(2):229–239.
- Zhang X, Zhang Q (2005) Online trust forming mechanism: Approaches and an integrated model. *Proc. 7th Internat. Conf. Electronic Commerce (ICEC '05)* (ACM, New York), 201–209.



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