Investigating the Nonlinear and Conditional Effects of Trust – The New Role of Institutional Contexts in Online Repurchase

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ABSTRACT

Trust is paramount to developing and maintaining long-term relationships in all stages of the customer lifecycle, including the repurchase stage. Going beyond the simple finding documented in the extant trust literature that the effect of trust will diminish, this research sheds light on the role of institutional contexts and develops a nuanced understanding of the boundary conditions under which trust operates in the repurchase stage, where knowledge-based trust becomes more predominant. Drawing on a different theoretical tenet, prospect theory, we find that customers exhibit distinctively different transaction intentions in the two perceptual conditions of high and low trust in institutional contexts. Specifically, the nonlinear relationship between trust and repeat online transaction intention is inverted U-shaped curvilinear when trust in institutional contexts is high; but is U-shaped when trust in institutional contexts is low. With data collected from both e-commerce and mobile banking contexts using two different measures of institutional contexts, we employed a new and advanced latent moderated structural equations (LMS) approach for analysis and provided robust results. Our findings largely confirm the hypotheses and offer theoretical, methodological, and practical implications.

Keywords: Trust, institutional contexts, structural assurance, e-commerce, mobile banking, prospect theory, latent moderated structural equations

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INTRODUCTION

After decades of development, the application of e-commerce has progressed to a more mature repurchase stage. Most companies nowadays have invested in online business and chosen to sustain business relationships with their customers online. They have made good use of emerging mobile and wireless technologies to encourage customers to conduct tasks such as managing bank accounts or replenishing products with IoT devices. Also, repeated transactions are the primary revenue for companies. Therefore, it is essential for companies to obtain an in-depth understanding of how customers develop repurchase intentions online.

When transacting in such an agile environment, customers face uncertainty associated with the vendor (e.g., retailer, bank, etc.) and the environment. Trust has long been understood as a key mechanism to mitigate customer uncertainty and assure online transactions (Gefen, Karahanna, & Straub, 2003b; Kim, Ferrin, & Rao, 2009a; Luhmann, 1979). It also plays an important role in long-term relationships and customer retention (Carter, Wright, Thatcher, & Klein, 2014; Gefen et al., 2003b; Jarvenpaa, Tractinsky, & Vitale, 2000; Pennington, Wilcox, & Grover, 2003). Despite the maturity of trust research, the effect of trust, however, has not yet received sufficient scholarly attention in the repurchase stage. It has been oversimplified as a diminishing nonlinear effect, as much evidence has agreed that the effect of trust would decay after passing a certain tipping point (Gefen, Benbasat, & Pavlou, 2008; Liu & Goodhue, 2012; Van der Heijden, Verhagen, & Creemers, 2003). Given the significance of customer retention and the role trust plays in long-term relationships, it is of great value to further investigate the boundary condition of the complex relationship between trust and repeat online transaction intention in repurchase.

Hence, in this research, we argue that trust in vendor exhibits a nonlinear effect on customer repeat online transaction intention in the repurchase stage, where the nonlinear effect is moderated by an important contextual condition: trust in institutional contexts. Institutional contexts in this research are defined as vendor-independent impersonal structures and mechanisms (e.g., guarantees, regulations, etc.) that are developed to safeguard and assure customer online transactions (McKnight, Choudhury, & Kacmar, 2002; Pavlou & Gefen, 2004; Thatcher, Carter, Li, & Rong, 2013; Zucker, 1986).

We propose trust in institutional contexts as an important boundary condition of such relationship in repurchase. First, trust in institutional contexts has changed to a moderating role when progressing from the initial purchase to the repurchase stage, where the function of the new role has not been formally theorized. In initial purchase, trust in institutional contexts is an *antecedent* for *building trust* in vendor (McKnight et al., 2002; Pavlou & Gefen, 2004). However, in repurchase, trust in institutional contexts serves as a *moderator*, *shaping* individuals' perceptions of how to *interpret* the vendor's behavior (Jarvenpaa, Shaw, & Staples, 2004; Lankton, McKnight, Wright, & Thatcher, 2016). Second and more importantly, the new role in the repurchase stage is bounded by a different *theoretical assumption* and *trust concern*, which may account for the inconclusive findings in the existing studies on the moderating role of trust in institutional contexts, that are premised on social exchange theory (arguably more related to initial purchase) (Chen, Huang, Davison, & Hua, 2015; Fang et al., 2014; Gefen & Pavlou, 2012).

In this research, we draw on a different theoretical foundation, namely prospect theory, and propose that it is more suitable for understanding how customers interpret a repeat online transaction decision in relation to trust in institutional contexts. First, when considering the role of institutional contexts in repurchase, prospect theory explains how individuals *frame* and *interpret* a decision based on the surrounding contexts – it suggests that individuals would rather perceive them in a positive or negative domain and act differently even for the same actual institutional contexts (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991). Second, prospect theory takes human psychology into consideration, for example, how individuals perceive and respond to *certainty* and *predictability*, an important concern in *repurchase*. Rather than maximizing self-interest rationally as in social exchange theory, prospect theory proposes that the value individuals perceive from a decision follows a nonlinear fashion – similar to how their psychological response changes (Kahneman & Tversky, 1979). The use of prospect theory thus represents a meaningful theoretical departure from most trust studies in the extant literature.

Therefore, we intend to answer the research question: *how does trust in institutional contexts moderate the nonlinear effect between trust in vendor and repeat online transaction intention?* Drawing on prospect theory, we propose that the nonlinear relationship could exhibit different patterns in two distinctive conditions (i.e., high and low trust in institutional contexts): it would be inverted U-shaped curvilinear when trust in institutional contexts is high; and U-shaped curvilinear when trust in institutional contexts is low. To test the complex nonlinear and conditional effects, we employed a new and advanced latent moderated structural equations (LMS) approach and conducted two empirical studies in e-commerce and mobile banking contexts using two measure proxies for trust in institutional contexts (structural assurance, perceived effectiveness of e-commerce institutional mechanisms) (Fang et al., 2014; McKnight et al., 2002) for robustness and generalizability. Our hypotheses were supported by the findings.

The contributions of this research are threefold. Theoretically, to the best of our knowledge, this research is one of the first to investigate the nonlinear and conditional effects of trust in a systematic theoretical framework. Our theorization with the new theoretical foundation in the two conditions of institutional contexts and the related empirical findings provide a more nuanced understanding of the operational boundary of trust in IS research, extending the understanding to the repurchase stage. Methodologically, this research is one of the few to systematically theorize and analyze nonlinear and conditional effects using an advanced LMS approach. It also discusses the benefits of LMS over existing approaches in extant IS studies and demonstrates how to apply LMS in analysis. Practically, we suggest to vendors the existence of these two valid yet contrasting conditions of trust in institutional contexts for which different strategies ought to be utilized to build trust and retain customers.

THEORETICAL FOUNDATION

Trust in Institutional Contexts in Initial Purchase and Repurchase Stages

In the general e-commerce and mobile environment, there are two types of trust. Trust in vendor is a specific trust towards the vendor and trust in institutional contexts is a general trust towards the environment (Thatcher et al., 2013). Trust in institutional contexts, commonly known as institution-based trust or institutional trust in IS research, represents a general trust belief in the environment that institutional mechanisms and structures are in place to safeguard customer online transactions (McKnight et al., 2002; Pavlou & Gefen, 2004; Thatcher et al., 2013; Zucker, 1986).

Trust in institutional contexts is a proxy of customer vulnerability in the online transaction environment (Gefen & Pavlou, 2012; Pavlou & Gefen, 2004). The belief could be high if customers perceive that the institutional contexts are effective (i.e., high condition of trust in institutional contexts). Similarly, the belief could be low when believing that the institutional contexts are less effective (low condition of trust in institutional contexts). Trust in institutional contexts is widely believed to be a perceptual term because the belief varies across customers – each of them may perceive the same actual institutional contexts to be high or low in effectiveness (Fang et al., 2014;

Gefen & Pavlou, 2012; McKnight et al., 2002; Pavlou & Gefen, 2004).

There are two types of institutional contexts – vendor-specific and vendor-independent (Fang et al., 2014). The former provides marketing and legal institutional structures (e.g., feedback mechanism, escrow service in Amazon marketplace) to tackle customer risks associated with a specific transaction or vendor (Gefen & Pavlou, 2012; Pavlou & Gefen, 2004). The latter, on the other hand, addresses risks lying in the general online transaction environment, for example, structural assurance (SA)[1] and perceived effectiveness of e-commerce institutional mechanisms (PEEIM)[2]. In this research, we denote trust in institutional contexts to be the vendor-independent type (e.g., SA, PEEIM) because they also address the contextual risks that are not covered in the vendor-specific type. These risks include losses from accidental clicks, browser refreshing, or network attacks and data breach in the online and mobile environment, which are generally beyond the vendors' control (Ghosh & Swaminatha, 2001; Grabner-Kräuter & Kaluscha, 2003; Siau & Shen, 2003).

According to the trust literature, different types of trust are salient in the initial purchase and repurchase stages, respectively. In the initial purchase stage, trust is fragile and calculus-based (Lewicki & Bunker, 1996; McKnight, Liu, & Pentland, 2020). Customers know little about the vendor, so they are skeptical about transacting with the vendor and are more willing to do so when benefits outperform costs in this transaction decision (Lewicki & Bunker, 1996; Liu & Goodhue, 2012). Trust in institutional contexts in this case usually serves as an *antecedent* to build initial trust because the third-party promises and guarantees in the institutional contexts reduce the

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[1] Structural assurance: "one believes that structures like guarantees, regulations, promises, legal recourse, or other procedures are in place to promote success (Shapiro, 1987; Zucker, 1986)." (McKnight et al., 2002, p.339)

[2] Perceived effectiveness of e-commerce institutional mechanisms (PEEIM): "an online customer's general perception that safeguards exist in the e-commerce environment to protect him/her from potential risks in online transactions." (Fang et al., 2014, p.410)

economic incentives for the vendor to act opportunistically, serving as a safety net for the transaction (McKnight & Chervany, 2006; McKnight et al., 2002; Pavlou & Gefen, 2004).

In the repurchase stage, knowledge-based trust becomes more salient when customers have developed first-hand knowledge about the vendor. After repeated transactions, customers start to engage in this type of relational trust and concern about mutual interest rather than maximizing self-interest in the previous stage (Rousseau, Sitkin, Burt, & Camerer, 1998). They are even willing to tolerate unmet expectations and may identify with the vendor in shared values in an extreme case (Lewicki, Tomlinson, & Gillespie, 2006). With knowledge-based trust, customers shift the emphasis to predictability – whether the vendor's behavior can be accurately anticipatable (Lankton et al., 2016; Lewicki & Bunker, 1996). In this stage, the role of trust in institutional contexts changes to that of *moderator,* adjusting the predictability and certainty of the outcome in repeat online transactions with the same vendor. Specifically, when customers are already familiar with and have gradually established trust with the vendor, the everchanging Internet and mobile transaction environments (with the new technologies and regulations) keep imposing new uncertainty on customers. This uncertainty constantly affects their trust in institutional contexts, thus influencing their interpretation and assessment of trust in vendor (Kim, Shin, & Lee, 2009b; Siau & Shen, 2003). Table 1 summarizes the key features of trust in these two stages.

Table 1. Trust in Initial and Repurchase Stages

	Initial Purchase Stage	Repurchase Stage
Trust Concerns		
Trust type	Calculus-based	Knowledge-based
Main concern	Reward/punishment	Predictability, certainty
Goal	Maximize self-interest	Pursue mutual interest
Trust in Vendor		
Uncertainty in the vendor	High, due to no experience	Relatively low, due to first-hand experience and familiarity
Trust effect	Mainly linear	Linear or nonlinear up to date

Trust in Institutional Contexts		
Uncertainty in the environment	Static	Dynamic and constantly changing
Role in the trust effect	Antecedent Trust in Institutional Contexts → Trust in Vendor → Initial Online Transaction Intention	Moderator Trust in Vendor → Repeat Online Transaction Intention ↑ Trust in Institutional Contexts
Function	Build trust in the vendor	Frame the situation and interpret the vendor's behavior

Although a few studies (Chen et al., 2015; Fang et al., 2014; Gefen & Pavlou, 2012) have noted the new moderating role of institutional contexts in IS research, the theorizing effort is still limited, and empirical findings are inconclusive. Some researchers (Chen et al., 2015; Fang et al., 2014), on the one hand, have assumed linearity and proposed a negative moderating effect: the effect of trust would be strong when trust in institutional contexts is low; and the effect would be weak when trust in institutional contexts is high. However, their findings are mixed and equivocal (found positive and negative moderating effect respectively in the empirical results). Gefen and Pavlou (2012), on the other hand, argued for a more complex quadratic moderating effect: the effect of trust would be the strongest when trust in institutional contexts is moderate; the effect would be weak when trust in institutional contexts is low or high. Yet their empirical results suggest the moderating effect to be non-significant.

These inconclusive findings may lie in their theoretical foundation, social exchange theory (SET), which is supposed to be more salient for calculus-based trust in initial purchase theoretically. This theoretical basis may have hindered our understanding of the boundary condition of knowledge-based trust in repurchase in three aspects. First, SET does not account for the new functional role of institutional contexts as a moderator in repurchase. Following the assumptions in SET, prior research has discussed the relative strength of trust in vendor versus trust in institutional contexts using the cost-benefit analysis – when trust in institutional contexts is strong, trust in vendor should be weak (Chen et al., 2015; Fang et al., 2014; Gefen & Pavlou, 2012). By still taking trust in institutional contexts as a direct component in the calculation, SET is unable to acknowledge trust's new moderating role in repurchase – that is how trust in institutional contexts shapes customers' perceptions in interpreting the current environment for their repurchase decisions.

Second, SET does not sufficiently reflect the new concerns in the repurchase stage and in knowledge-based trust. According to SET, in the initial purchase stage, customers are concerned about self-interest and reciprocation with similar value received; therefore, this relationship is also called an exchange or transactional relationship (Blau, 1964; Clark, Powell, & Mills, 1986; Lewicki et al., 2006). But, when customers move to the long-term relationship in repurchase, they are not only driven by rationally maximizing self-interest in SET – they also think about the mutual interest and they value predictability and hence show different preferences for certainty (Lewicki & Bunker, 1995; Lewicki et al., 2006; Rousseau et al., 1998). Gefen & Pavlou (2012) also urged that these intangible social elements need to be realized in institutional contexts.

Third, SET is unable to reveal the pattern of how the effect of trust changes in repurchase. By discussing the relative strength of trust in vendor versus the one in institutional contexts, SET can only suggest the tipping points when trust enters the decision. While the field is calling for a more nuanced understanding of how trust changes in boundary conditions (Gefen & Pavlou, 2012; McKnight, Liu, & Pentland, 2014; McKnight et al., 2020), we address this deficiency by drawing on a different theoretical basis, prospect theory. Table 2 summarizes the contribution of the current study vis-à-vis other notable studies in relation to trust in institutional contexts.

Table 2. Comparison with Existing Studies of Trust in Institutional Contexts

		Existing Studies	This Research
Initial Purchase Stage	**Direct Effect**	(McKnight & Chervany, 2006; McKnight et al., 2002; Pavlou & Gefen, 2004).	
Repurchase Stage	**Moderating Effect**	Linear/quadratic moderating effect (Chen et al., 2015; Fang et al., 2014; Gefen & Pavlou, 2012)	Moderating effect on the nonlinear effect of trust
	Focus	Whether the linear effect of trust is *weak or strong* in high and low conditions of trust in institutional contexts	How the nonlinear effects of trust *change* in high and low conditions of trust in institutional contexts, respectively
Theoretical Basis		Social exchange theory	Prospect theory

Prospect Theory

Prospect theory is a seminal work in decision-making, explaining how individuals frame a decision based on the surrounding contexts and how they evaluate the decision outcome with bounded rationality (Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1991).

According to the theory, a reference point, also known as the current context an individual is exposed to, affects how the individual perceives the decision. It suggests that this decision could differ, often with competing outcomes, depending on how the context is framed within two different perceptual domains (positive or negative) (Hardin & Looney, 2012; Kahneman & Tversky, 1984; Looney & Hardin, 2009; Looney & Hardin, 2020). In a classic life-saving experiment, individuals positioned themselves in a positive domain if the decision problem highlighted benefits (lives saved) but reversed to a negative domain when the problem was negatively worded (no people will be saved) for the same problem (Tversky & Kahneman, 1981). The framing concept has been widely examined in marketing and IS studies where customers position themselves in a positive domain if the context is positively framed (e.g., highlighting gains, savings, assurances, or advantages). Conversely, customers/users position themselves in a negative domain if negative outcomes are expected (e.g., losses, risks, or uncertainty) (Chen & Liang, 2006; Chiu, Wang, Fang, & Huang, 2014; Fang et al., 2014; Grewal & Lundsey-Mullikin, 2006; Hardin, Looney, & Moody, 2017). The decision outcome would be regarded as gains in the positive domain and losses in the negative domain, respectively (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

Considering human psychology, prospect theory suggests that individuals do not always pursue self-interest maximization rationally – instead they overweight the option with certainty, which is called the certainty effect (Kahneman & Tversky, 1979). The same attitude for certainty is found in positive and negative domains, that is, individuals prefer sure gains over probable gains in the positive domain and prefer probable losses over sure losses in the negative domain. Therefore, the value curve is reversed in these two domains (reflection effect).

The value curve in prospect theory follows a nonlinear diminishing fashion (see Figure 1 for an illustration). It is because individuals evaluate the decision outcome (gains/losses) as a value function similar to how they react to changes in psychological responses (e.g., sensory dimensions, wealth status) – thus the value function would diminish (Kahneman, 2011; Kahneman & Tversky, 1979). For example, the same unit change of light in a bright room may exert a lesser impact on perception than in a dark room. The same unit change of water temperature in hot water may also exert a lesser impact than it would in cold water because individuals have adapted to the changes and their sensitivity diminishes (Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1991). In a similar vein, the same unit change of wealth, say, a gain of $100, may make a smaller subjective difference to individuals in moving from $1,000 to $1,100 than it would to individuals moving from $100 to $200. Similarly, a loss of $100 may produce less pain in moving from -$1,000 to -$1,100 than it would from -$100 to -$200 (Kahneman, 2011; Kahneman &

Tversky, 1979). This is because of diminishing sensitivity, wherein "the marginal value of both gains and losses decrease with their size" (Tversky & Kahneman, 1991, p.1039-1040).

In economics, it has been well established that the value function in the positive domain is concave (inverted U-shaped), implying that the value contributed by a unit change of decision outcome becomes smaller and smaller (Kahneman & Tversky, 1979). Losses diminish in the negative domain (from the reference point to negative infinity), but the value function in the negative domain is convex (U-shaped), meaning that the value contributed by a unit change of decision outcome becomes larger and larger (from negative infinity to the reference point). The right-hand panel of Figure 1 visualizes the change patterns of the two curves in respective domains.

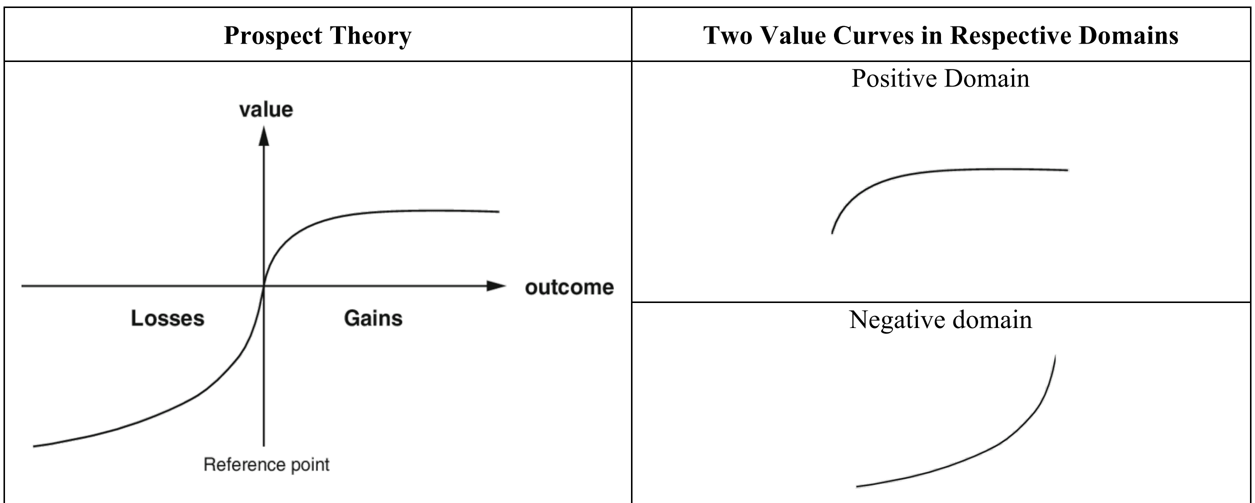

Figure 1. Illustration of Value Curves in the Positive and Negative Domains

HYPOTHESES DEVELOPMENT

Trust in Institutional Contexts: High Condition

As per prospect theory, in the respective high and low conditions of trust in institutional contexts, customers assess the effect of trust in vendor in relation to the context. That is, to frame a decision, customers refer to the surrounding context – institutional contexts in this case – to set the reference point for their current position. How the decision outcome changes their current position is dependent on how customers perceive the effectiveness of the institutional contexts (high versus low) in mitigating risks associated with their repurchase decision. As discussed, customers transacting in the same institutional contexts may perceive the contexts to be effective or ineffective (high or low in effectiveness) and hold different trust beliefs, ending up in two different perceptual domains (Kahneman & Tversky, 1984).

In situations where trust in institutional contexts is high, customers are unsure about the online transaction environment and the technologies associated with it, but they are knowledgeable about their rights protected by the institutional contexts. They generally believe that the impersonal institutional-based structures are effective in mitigating risks and safeguarding their online transactions because they are surrounded by institutional-based assurances such as government-regulated return and refund policies, law-enforced data protection regulations, and independent body regulation and accreditation programs (Yousafzai, Pallister, & Foxall, 2005), which all emphasize positive decision outcomes from transacting in institutional contexts. In such situations, customers are thus more likely to self-position in the *positive domain* and pay attention to *gains* in the repurchase decisions.

An effective institutional context offers general protections and guarantees for transactions with *any* vendors in this environment. For example, to address the concerns of product risk (Kim, Ferrin, & Rao, 2008), customers can seek assistance from escrow services to rectify the situation if the vendor has not delivered goods as promised. Under the EU rules, customers have the right to cancel and return an online order within 14 days and are entitled to receive a repair, replacement or refund if the goods are found faulty.[3] In the US, customers are protected by both federal and state laws, where they can return an item within 30 days of purchase in the State of New York, for

[3] https://europa.eu/youreurope/citizens/consumers/shopping/guarantees-returns/index_en.htm

example, even if the vendor does not have a return policy.[4] Federal law allows customers paying by credit card to temporarily withhold payment during an investigation and have limited liability for an unauthorized transaction.[5] Customers can also have recourse to an independent regulatory body such as the Financial Conduct Authority in the UK in the event of a misdirected payment or other financial irregularity. To further mitigate the information and financial risk concerns in the online environment, retailers and banks in some countries have been urged to implement strong customer authentication (SCA) for compliance (e.g., a two-factor authentication process).

Given the comprehensive protections by the institutional contexts, experienced customers in the repurchase stage know that they have been well protected by the contexts. Any additional assurance and promise from the vendor would provide little new information to enhance the predictability, because customers have been adapted to the certainty offered by the highly effective institutional contexts. In such a circumstance, customers may thus derive further less and less value with every increase unit of trust in vendor on their repeat transaction intention because their sensitivity towards the value diminishes – in a similar manner as they would react in a psychological response scenario (see earlier examples) (Kahneman, 2011; Kahneman & Tversky, 1979). Taken together, we argue that in situations when trust in institutional contexts is high, a unit increase in trust in vendor would lead to an increase in repeat online transaction intention at a decreasing rate, exhibiting a tendency towards an inverted U-shaped curvilinear relationship (Haans, Pieters, & He, 2016), because according to prospect theory, the changes of gains follow a concave pattern in the positive domain (see Figure 2).

[4] https://www.dos.ny.gov/consumerprotection/consumer_resources/3r.html
[5] https://www.consumer.ftc.gov/articles/0020-shopping-online

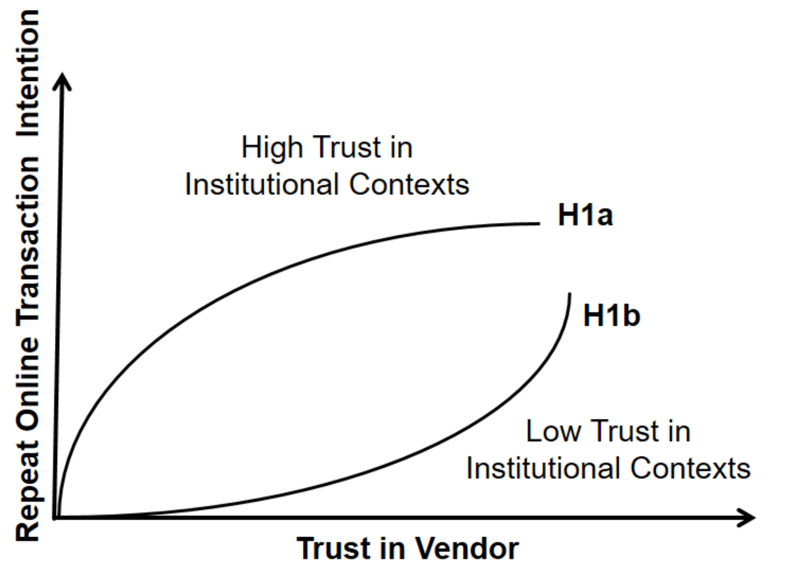

Figure 2. Illustration of Hypothesis 1

Trust in Institutional Contexts: Low Condition

It is understood that customers could have different perceptions regarding the effectiveness of institutional contexts (Tversky & Kahneman, 1981). When customers are uncertain about the transaction environment in the repurchase stage, they also rely on the available information and recent experience (Hogarth & Kunreuther, 1989). Customers who have recently experienced data breaches or who have attempted the reclaim process are likely to perceive the institutional contexts to be low in effectiveness because they have identified more risks involved, such as privacy risk (loss of control over personal privacy), time risk (additional time involved in the rectification), and psychological risk (psychological discomfort and losses in the process) (Featherman & Pavlou, 2003). Hence, in situations where trust in institutional contexts is low, customers are likely to perceive the transaction environment to be risky or lacking in protection. They are highly vulnerable to negative outcomes (i.e., *losses*) as a result of transacting in this environment and therefore position themselves in the *negative domain*.

Under such conditions customers are likely to remain alert and seek ways to reduce their vulnerabilities or losses, because according to prospect theory, humans in general are loss averse (Kahneman & Tversky, 1979). Transacting with a trustworthy vendor is one strategy they could use to largely save them from losses. Based on their first-hand interaction experience with the vendor, customers would appreciate a vendor's trust-reinforcement activities, such as keeping promises or following an investigation case seriously. The reputation and size of the vendor can affect customers' confidence in the vendor (Jarvenpaa et al., 2000). So too can the vendor's return options via offline networks to eliminate or reduce customer risk concerns and complements the vendor's online sales efforts (Kumar, Mehra, & Kumar, 2019). In this negative condition, customers overweight certainty such as facts and their own knowledge about the vendor because these enhance predictability in knowledge-based trust in repurchase (Kahneman & Tversky, 1979; Lankton et al., 2016; Lewicki & Bunker, 1996). As a result, with every successful loss-mitigating action conducted by the vendor, customers perceive a further greater value in these trust activities and increase their repeat transaction with that vendor accordingly.

Thus, we argue that in situations when trust in institutional contexts is low, a unit increase in trust in vendor would lead to an increase in repeat online transaction intention at an increasing rate. In short, we expect that the effect of trust on repeat online transaction intention will have a tendency to be U-shaped curvilinear because, according to prospect theory, the changes of losses follow a convex pattern in the negative domain. Therefore, we hypothesize:

> **H1.** Trust in institutional contexts moderates the nonlinear relationship between trust in vendor and repeat online transaction intention, such that the nonlinear relationship between trust in vendor and repeat online transaction intention is **(a)** inverted U-shaped curvilinear when trust in institutional contexts is high; and **(b)** U-shaped curvilinear when trust in institutional contexts is low.

METHODOLOGY AND DATA ANALYSIS

We collected data using the survey method because it is best suited for understanding individual perceptions, and it is strong in generalizability of research findings (Saunders, Lewis, & Thornhill, 2009). Specifically, we conducted two surveys in the United Kingdom (UK) and New Zealand in the contexts of mobile banking and e-commerce using two different measures of trust in institutional contexts (SA and PEEIM) for robustness purposes.

Study 1

In Study 1, we collected data in a mobile banking context where banks are keen to retain customers' online transactions and trust is a critical concern (Kim et al., 2009b; McKinsey&Company, 2017; Montazemi & Qahri-Saremi, 2015).

The questionnaire had three main sections. First, respondents were presented with a series of questions regarding their general perceptions of the mobile banking environment (i.e., trust in institutional contexts). In the second section, respondents were asked to recall the bank that they used most frequently to conduct their personal financial transactions and the questions that followed focused on their mobile banking activities, interaction frequency, their trust in the bank (i.e., trust in vendor) and their future intention to stay with that bank and use their mobile-banking service (i.e., repeat online transaction intention). The final section included profile-related information. The survey was piloted in a university in the UK, followed by minor adjustments.

We adapted the principal constructs of theoretical interest – trust in vendor (Einwiller, 2003; Fang et al., 2014; Garbarino & Lee, 2003; Jarvenpaa et al., 2000), trust in institutional contexts (e.g., SA) (McKnight et al., 2002), and repeat online transaction intention (Fang et al., 2014; Jarvenpaa et al., 2000) – from the existing literature to enhance validity. Several control variables were included to ensure that the empirical results were not caused by covariance with other variables. These included perceived risk in the general online environment, experience using mobile banking (m-banking), gender, age, and income level. This approach is consistent with several related prior studies (Fang et al., 2014; Qureshi et al., 2009; Van Slyke, Comunale, & Belanger, 2002; Zhang et al., 2011). Appendix A lists the measurements.

To test our hypotheses in the mobile banking context, in this Study 1, we recruited respondents from two universities in the UK because mobile banking penetration in the UK is growing fast (79% in 2019) and that the young generation accounts for almost 80% of the total UK mobile payment users (Statista, 2020). As a screening check, before taking part, respondents must have used at least one of the mobile banking activities listed in the introductory section of the questionnaire (e.g., check multiple accounts, 24/7 access, check balances, transfer funds, schedule payments, receive alerts, pay bills, or schedule transfers) via a mobile banking application or mobile banking website. Respondents could receive a cash voucher for participating in the survey. We obtained 220 usable responses from university A (response rate: 67%) and 224 responses from university B (response rate: 86%), resulting in an overall sample of 444 (response rate: 76%). T-tests did not find any statistical differences between the two sub-samples on any of the demographic variables or principal constructs of theoretical interest. On average, the relationship with the most-frequently used banks ranged from three to five years.

Data Analysis: Latent Moderated Structural Equation (LMS)

Covariance-based structural equations modeling (CBSEM) (Bollen, 1989; Qureshi & Compeau, 2009) was used to test the confirmatory factor analysis (CFA) and the structural model. CBSEM was chosen in this research for its strength in providing unbiased parameter estimates, overall model fit, nested model comparisons (Anderson & Gerbing, 1988; McIntosh, Edwards, & Antonakis, 2014), and advanced modeling techniques for nonlinear and interaction effects

(Dimitruk, Schermelleh-Engel, Kelava, & Moosbrugger, 2007; Klein & Moosbrugger, 2000). Mplus version 7 was used for the analysis (Muthén & Muthén, 2013).

To test the hypothesized quadratic effects and latent interactions, we used the latent moderated structural equation (LMS) approach (Klein & Moosbrugger, 2000; Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009). Researchers using CBSEM face difficulties in performing interactions between latent variables (Ping, 1996). For latent constructs, scholars traditionally compute summated scores, i.e., combine all the items of the constructs to create an index and then use that index in moderated multiple regression (e.g., Shalley, Gilson, & Blum, 2009; Wang, Tomlinson, & Noe, 2010). In such cases, a reasonably high reliability index, assessed using an internal consistency measure such as Cronbach's alpha (> 0.7), is often used as justification for summation. However, this approach assumes an equal weighting of items: "this implies all items are equal in their contribution towards estimating the interaction effect" (Chin, Marcolin, & Newsted, 2003, p. 190). Such an approach compromises the measurement model and therefore provides a less optimal solution.

To address this shortcoming, Kenny and Judd (1984) proposed a latent interaction (LI) approach for CBSEM where the indicators of latent constructs (predictor and moderator) are cross-multiplied to create "indicators" for the latent interaction construct. There are other variants of this method (Bollen & Paxton, 1998; Jöreskog & Yang, 1996; Ping, 1996). Although this method has been employed in some studies (e.g., Hult, Ketchen, & Arrfelt, 2007; Jöreskog & Yang, 1996; Kenny & Judd, 1984; Lee & Peccei, 2007; Song, Droge, Hanvanich, & Calantone, 2005), its application remains limited for several reasons: it is technically demanding; setting linear and nonlinear constraints is a cumbersome process; constraints grow exponentially as the number of indicators for predictor and moderator variables increases; setting constraints often results in analytical errors (Bollen & Paxton, 1998; Li et al., 1998; Ping, 1996; Williams, Vandenberg, & Edwards, 2009); and give rise to the conundrum of reliability and multicollinearity (see Appendix G). Researchers also coped with this issue in Partial Least Squares SEM (PLS-SEM).[6]

Table 3. Existing Approaches on Testing Interaction Effects

Approaches		Problems
Covariance-based SEM (CBSEM)	Summated score	• Assumes an equal weighting of items • Compromised measurement model • Less optimal solution
	Latent interaction (Product indicator)	• Technically demanding • Cumbersome process of setting constraints • Analytical errors • The conundrum of reliability and multicollinearity (see Appendix G)

In order to address the methodological issues mentioned above (Table 3), we implemented an advanced technique developed by Klein, Moosbrugger and colleagues to estimate latent interactions (Dimitruk et al., 2007; Klein & Moosbrugger, 2000; Klein, Moosbrugger, Schermelleh-Engel, & Frank, 1997; Klein & Muthén, 2007; Klein & Stoolmiller, 2003; Moosbrugger, Schermelleh-Engel, & Klein, 1997; Schermelleh-Engel, Klein, & Moosbrugger, 1998; Schermelleh-Engel et al., 2010): a latent moderated structural equations (LMS) approach. To the best of our knowledge, no paper published in the "Basket of 8 top IS journals" has used this LMS approach up until now, with the one exception of Fang et al. (2014) who applied it for a

[6] Chin et al. (2003) implemented Kenny and Judd (1984) approach in partial least squares – product indicator (PLS-PI). Several studies, especially in the field of IS, have used PLS-PI for latent interactions (e.g., Sarker & Valacich, 2010; Tiwana & Konsynski, 2010). However, Goodhue et al. (2007) in a Monte-Carlo simulation study suggested that PLS-PI capitalized on chance, a claim that was supported by Rönkkö (2014) (see also Goodhue, Lewis, & Thompson, 2012; Rönkkö & Evermann, 2013). In another study, Schermelleh-Engel, Werner, Klein, and Moosbrugger (2010) found that PLS-PI estimates for linear and interaction parameters were downward biased. It has also been criticized for "not being able to avoid incorporating errors" (Bentler & Huang, 2014; Hwang, Ho, & Lee, 2010; Rigdon, 2012). Moreover, it does not provide any overall model fit indices to compare the interaction model with the main effect model (Bentler & Huang, 2014; Hwang et al., 2010). PLS-PI thus appears to be an easy-to-implement but less optimal solution for latent interactions.

robustness check, mentioning it only very briefly in a footnote. We provide a detailed account of the LMS approach in this paper.

LMS facilitates a robust estimation of interactions between latent variables using maximum likelihood and finite mixture extensions of standard latent variable models (Klein & Moosbrugger, 2000). LMS can be thus used to test whether the influence of a latent (independent) variable on another latent (dependent) variable is moderated by a third latent variable. Like Kenny and Judd's (1984) method for latent interactions, LMS takes measurement reliability into account – an issue that has been largely neglected by traditional approaches such as moderated regression analysis (Aiken & West, 1991) – thereby improving accuracy in detecting interaction effects. Moreover, this method is easy to implement as it directly estimates an interaction effect and: (1) does not require researchers to specify cumbersome linear and nonlinear constraints; (2) does not require the computation of residual terms; (3) does not require the application of nonlinear weights or multiplication of indicators (Klein & Moosbrugger, 2000) (see Appendix G for additional information on this); and (4) help resolve the conundrum of reliability and multicollinearity present in product indicator based approaches (see Appendix G for additional information on this).

The LMS approach for modeling the interactions of latent factors properly accounts for the non-normality of factors that are inherent in latent interaction models, and its maximum likelihood estimators exhibit desirable asymptotic and finite-sample statistical properties (Klein & Moosbrugger, 2000; Moosbrugger et al., 1997). The LMS method has been shown to do well in simulations (Little & Rubin, 2002; Marsh, Wen, & Hau, 2004), generally outperforming alternative approaches for addressing interactions amongst latent variables (Klein & Moosbrugger, 2000; Marsh, Wen, & Hau, 2006; Moosbrugger et al., 2009; Schermelleh-Engel et al., 1998; Schermelleh-Engel et al., 2010; Wen, Hau, & Marsh, 2003) and is regarded as "the most efficient maximum likelihood method" (Dijkstra, 2014, p.149). It uses maximum likelihood estimation with robust standard errors (henceforth MLR). LMS produces true ML estimates that are robust and efficient (Brandt, Kelava, & Klein, 2014; Kelava et al., 2011). These and other simulation studies have consistently revealed the superiority of the LMS method in comparison to other available methods with regards to efficiency, robustness and unbiasedness of parameter estimations (Dimitruk et al., 2007; Kelava, Moosbrugger, Dimitruk, & Schermelleh-Engel, 2008; Schermelleh-Engel et al., 2010). LMS is easy to implement with advanced statistical software such as Mplus (Muthén & Muthén, 2013), which is used in this research. In Mplus, the LMS approach involves employing the use of numerical integration with the expectation-maximization (EM) algorithm to obtain maximum likelihood estimates of model parameters.

Table 4. General Strategy to Test the LMS Model Fit

Step	Criteria
1. Assess the model fit for the main effect model	• Comparative fit index (CFI), Tucker-Lewis index (TLI) • Root mean square error of approximation (RMSEA)
2. Assess the interaction effect over the main effect model	• Contributions of interaction effects: log likelihood difference test ($\Delta 2LL$) • Model fit: Improvement in Bayesian information criterion (BIC), Akaike information criterion (AIC), and sample-size adjusted BIC (SABIC)

As typical fit indices are not available for an LMS model, we provide a general strategy to test the model fit (Table 4). The first step is to ensure that there is a good model fit for the main effect model. Second, one must assess the contribution of the interaction effect using the log likelihood difference test ($\Delta 2LL$). A significant log likelihood difference test indicates that the interaction effect contributes over and above what is explained by the main effect model. Other criteria used for judging model fit are: Bayesian information criterion (BIC); Akaike information criterion (AIC); and sample-size adjusted BIC (SABIC) (Burnham & Anderson, 2004; Kuha, 2004; Qureshi & Fang, 2011). For example, smaller BIC values indicate better model fit. Later in the structural model section, we demonstrate how to apply this strategy.

Measurement Model

We conducted confirmatory factor analysis (CFA) following the standard procedure (Schumacker & Lomax, 2004) to ascertain whether all the items of the corresponding construct loaded together. Appendix A presents the construct items and their loadings. All factor loadings were above the recommended levels of 0.7, except for the loading of one item for repeat online transaction intention (0.65).[7] The fit indices for confirmatory factor analysis were better (CFI = 0.979, TLI = 0.974, RMSEA = 0.051, SRMR = 0.027) than the recommended levels in the literature (Hu & Bentler, 1999; Marsh et al., 2004).

Internal consistency reliabilities (ICR), average variance extracted (AVE), and construct correlations are presented in Appendix B. All the AVE values were greater than 0.5 and all the ICRs were far above the standard threshold of 0.7 (Carmines & Zeller, 1979). To assess discriminant validity, the AVE and matrix of loadings and cross loadings were examined (Fornell & Larcker, 1981). The correlation between each pair of constructs was lower than the square root of the AVE of either of those constructs. None of the cross-loadings exceeded the recommended level, indicating that items loaded onto their own construct. All the constructs therefore passed the criteria of discriminant validity. This test also provides evidence that there is limited threat of multi-collinearity (Jagpal, 1982) and common method bias (Hanisch, Hulin, & Roznowski, 1998).[8]

[7] Considering that the ICR for the online transaction intention construct is .83 and square root of AVE is .79 and that the loading of the item in is only marginally lower than the guideline, we decided to keep this item in the model.

[8] We also used Harman's single-factor approach to test common methods bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff & Organ, 1986). We included all items of the latent variables in our model. A single factor did not emerge from this analysis and the first factor, representing trust in bank, explained only 49% of the variance in the model. This was expected, as out of 15 items, eight were associated with trust in bank. There were three factors with eigenvalues over 1.0, which collectively explains 77% (cumulative) of the variance. The analysis confirms that the threat of common method bias is minimal (Lindell & Whitney, 2001; Richardson, Simmering, & Sturman, 2009).

Structural Model

Following established norms, we used multiple fit indices to evaluate model fit for the structural model (Bollen, 1989; Little & Rubin, 2002). The goodness of fit for each model was examined using two incremental close-fit indices: comparative fit index (CFI) and Tucker-Lewis index (TLI), in addition to the root mean square error of approximation (RMSEA) (Bollen, 1989; Goldstein, 2011). Incremental fit indices (CFI and TLI) of 0.95 or higher reflect acceptable levels of fit. A RMSEA score less than 0.08 indicates reasonable errors of approximation; and a score of less than 0.05 represents a close fit (Hu & Bentler, 1999; Marsh et al., 2004). All the models satisfied these requirements.

Table 5 provides results of the structural model. Model-1 only includes the control variables. In Model-2, we added trust in bank and SA. Although not explicitly hypothesized, both of these variables had a positive relationship with the dependent variable: repeat online transaction intention. This is consistent with past findings in the literature (Fang et al., 2014; Qureshi et al., 2009; Zhou, 2013), providing us with confidence to continue with our analyses. In Model-3, we introduced the nonlinear effects of trust. We found the β for the nonlinear effect of trust to be negative and significant (β= -0.14^{*}), supporting our premise that trust exhibits a nonlinear effect on repeat online transaction intention. Furthermore, as illustrated in Model-4, the moderating effect of SA was significant on the linear (i.e., β for SA*Trust) and nonlinear effect of trust (i.e., β for SA* $Trust^2$). These effects were respectively -0.06^{+} and -0.10^{*}, confirming a significant moderating effect on the nonlinear relationship.

Table 5. Results of Nested Structural Equations Models				
	Model-1	**Model-2**	**Model-3**	**Model-4**
Control Variables				
--Risk	-0.00	0.00	0.00	0.00
--M-banking Experience	0.06^{*}	0.02	0.02	0.01
--Gender	0.11	0.05	0.05	0.05
--Age	-0.07^{+}	-0.03	-0.03	-0.02
--Income	-0.02	-0.00	-0.00	-0.00
Trust in Bank (Trust) (β1)		0.34^{***}	0.32^{***}	0.31^{***}
Structural Assurance (SA) (β5)		0.16^{***}	0.15^{***}	0.15^{***}
Trust^2 (β2)			-0.14^{*}	-0.13^{*}
SA*Trust (β3)				-0.06^{+}
SA* Trust^2 (β4)				-0.10^{*}
Fit indices				
χ^2 (df)	19.96 (9)	314.61(154)		
CFI	.980	.972		
TLI	.960	.968		
RMSEA	.052	.048		
SRMR	.023	.038		
AIC	3260.16	19774.02	19764.66	19748.17
BIC	3321.60	20048.44	20043.17	20035.88
SABIC	3273.99	19835.81	19827.37	19812.73
Free parameters	15	67	68	70
H_0-value	-1615.08	-9819.01	-9814.33	-9803.09
H_0- Scaling Correction Factor for MLR			1.6043	1.6262
$\Delta\chi^2$ using correction factor				9.482
p-value ($\Delta\chi^2$)				0.009
Turning point (β1*β4 - β2*β3) move to the left as SA increases				-0.0388
Flipping point (- β2/ β4)				-1.3
Note: Nonlinear and interaction effects were estimated using LMS ***p<0.001, **p <0.01; *p <0.05; +<0.1; Steepening of inverted U shape as β2 and β4 both are negative. R^2 (Model 1) = 0.049; R^2 (Model 2) = 0.331; R^2 (Model 3) = 0.395.[9]				

[9] When there are latent interactions with a latent interaction terms (i.e., Z interaction with X * X, which is a technically a latent interaction of X and X), we do not get R-Squared but Chi-Square test provide significance of variance explained. Thus, we do not get R-Squared for model 4. Same for the models in Tables C1 and F1.

We compared AIC, BIC and SABIC values for models with the main effects (Model 2), quadratic effect (Model 3) and interaction term (Model 4). We found that all three criteria had significantly[10] smaller values for the models with the interaction term compared to those that did not (Burnham & Anderson, 2004). This indicates an overall improvement in model "fit" with the interaction term as well as a significant contribution of the interaction effect over and above the main effect model.[11]

In order to estimate the substantive contribution of the interaction terms, we used the Satorra-Bentler chi-square difference test based on loglikelihood values and scaling correction obtained with the MLR estimator (Satorra, 2000; Satorra & Bentler, 2010). The interaction effects were not only significant, but substantive as indicated by the Satorra-Bentler chi-square difference test based on loglikelihood values and scaling correction factors ($\Delta\chi$ = 9.482, p-value = 0.009). This indicates that trust in institutional contexts exerts a significant negative moderating effect on the nonlinear relationship between trust in vendor and repeat online transaction intention. Specifically, the nonlinear effect of trust on repeat online transaction intention is inverted U-shaped curvilinear when SA is high (SA = μ+1.33 SD); but is U-shaped curvilinear when SA is

[10] The expression $e^{((AICmin - AICc)/2)}$ provides a test for probability that the comparison model (i.e., AICc) minimizes the estimated information loss. This is known as relative likelihood of AICc model. In our case, the AICmin is Model 4 and it is being compared with Model 2 ($AICc_1$) and Model 3 ($AICc_2$). AIC for Model 4 is 19748.17 and that for Model 2 is 19774.02, thus the Model 2 is 0.0000024 ($e^{((19748.17 - 19774.02)/2)}$) times as probable as Model 4 to minimize the information loss. Similarly, the Model 3 is 0.00026 times as probable as Model 4 to minimize the information loss. Thus, Model 4 is selected over Model 2 and Model 3. In general the ΔAIC (i.e., AICc – AICmin) less than 2 indicate that the two models cannot be distinguished, ΔAIC greater than 2 but less 5 indicates AICmin model is preferred but other criteria such as sample size and construct complexity (i.e., number of items, multiple dimensions among others) need to be taken into account. AIC greater than 5 indicate AICmin model should be accepted as a more information preserving model. AIC greater than 10 clearly establishes superiority of AICmin model (Burnham & Anderson, 2002, 2004; Huang, 2017; Lin, Huang, & Weng, 2017).

[11] There are two things important to note about AIC comparison. First, AIC can be used for nested or non-nested models. Second, model complexity should be comparable in order to implement relative likelihood AIC approach. Model complexity can be judged based number of constructs being used and reported free parameters. Thus, based on these criteria, it will not be appropriate to use Model 1 in such a comparison.

low (SA = μ-2.36 SD). We present these nonlinear interaction effects in Figure 3, which shows two distinct patterns in the different perceptual institutional contexts.

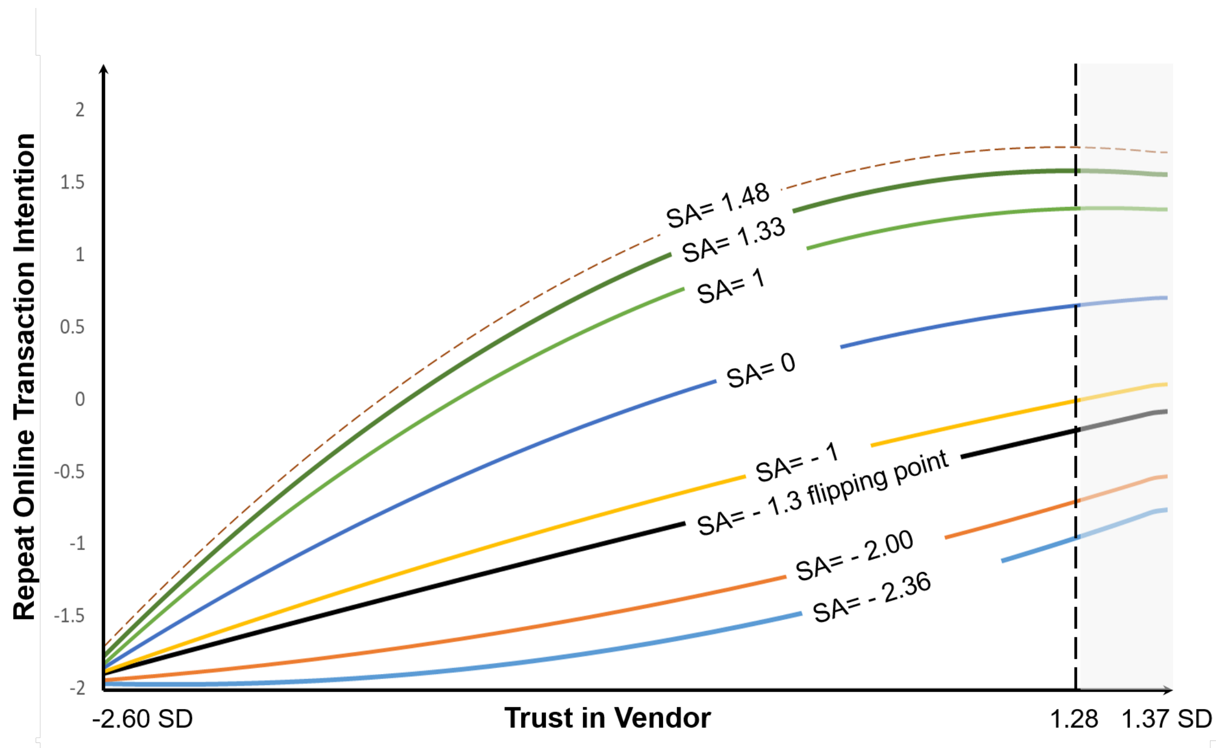

Figure 3. Nonlinear Interaction Effects

(Note: μ=0, and SD=1 for all the latent variables used in this figure. Consistent with Haans et al. (2016) recommendations, the possible and observed range of variables have been used in the Figure. For trust in vendor 1.37 SD was possible upper limit of the variable but the highest observed value was 1.26 SD. Similarly, for SA 1.48 SD was possible upper limit of the variable but the highest observed value was 1.33 SD)

Post-Hoc Analysis

To understand the nonlinear relationship in-depth, we followed the approach proposed by Haans et al. (2016) for testing the inverted U-shaped relationships between trust and repeat online transaction intention as well as the moderating effect of SA on this relationship. In order to understand the movement of the turning point, we calculated the term β1*β4 - β2*β3 which was -0.0388 (see Table 5), indicating that the turning point moves to the left as SA increases. This movement in turning point can be verified from Figure 3 for the inverted U-shaped curve (i.e., for SA= -1, 0, 1, and 1.33). Further, β2 was negative, indicating an inverted U-shaped nonlinear main effect, and β4 was also negative, indicating a negative moderating effect on the nonlinear relationship. As both β2 and β4 are negative, this indicates the steepening of the inverted U shape (which can be seen in Figure 3); and as SA increases for SA> -1, the inverted U-shaped curve steepens.

When an inverted U-shaped curve steepens for the increasing value of a moderator (in this case SA), it may flip its shape for the lower value of SA within the data range and become U-shaped (Haans et al., 2016, p.1190). To assess that possibility, we also calculated the term –β2/β4, which was -1.3 (see Table 5), indicating a flipping of the curve at SA= -1.3. As SA was standardized with mean=0 and SD=1, the value -1.3 indicates the SA value of mean -1.3 SD, which was well within the data range. The flipping of the curve can also be seen in Figure 3. For SA=-1.3, the line is straight; for values lower than -1.3 the curve is moderately U-shaped; and for values higher than -1.3, the curve becomes increasingly inverted U-shaped.

Replication Analysis: Additional Analysis Using PEEIM

For robustness, we repeated our analysis with another measure of trust in institutional contexts, PEEIM (instead of SA), in the analysis reported above. We provide items loading of PEEIM in Appendix A. All the items had loading above recommended level of 0.7. We provide correlation of PEEIM with other variables in Appendix B.

Table C1 in Appendix C provides results of the structural model. Model-1 only includes the control variables. In Model-2, we added trust in bank and PEEIM. Although not explicitly hypothesized, both of these variables had a positive relationship with the dependent variable: repeat online transaction intention. This is consistent with past findings in the literature (Fang et al., 2014; Qureshi et al., 2009; Zhou, 2013), as well as the result obtained with SA in this study. In Model-3, we introduced the nonlinear effects of trust. We found the β for the nonlinear effect of trust to be negative and significant (β= -0.15*), supporting our premise that trust exhibits a nonlinear effect on repeat online transaction intention. Furthermore, as illustrated in Model-4, the moderating effect of PEEIM was significant on the linear (i.e., β for PEEIM*Trust) and nonlinear effect of trust (i.e., β for PEEIM* Trust^2). These effects were respectively -0.09* and -0.13*, confirming a significant moderating effect on the nonlinear relationship. The nonlinear interaction effects have been presented in Figure C1 in Appendix C.

Study 2

To enhance robustness and generalizability, in Study 2, we collected data using the PEEIM measure from university personnel in New Zealand on their e-commerce repurchase behaviors. The respondents who had prior experience of purchasing a product or services online for personal use were requested to complete the questionnaire. The respondents were asked at the beginning of the questionnaire to think of an online vendor that they have purchased from recently. A total of 383 questionnaires were returned with an overall response rate of 30%.[12]

We provide information on construct items and their loadings in Appendix D. All the items loadings were above 0.7 except one item loading of PEEIM, which was 0.69. We provide correlations, reliability scores, and AVE in Appendix E.

Table F1 in Appendix F provides results of the structural model. Model-1 only includes the control variables. In Model-2, we added trust in vendor and PEEIM. Although not explicitly hypothesized, both of these variables had a positive relationship with the dependent variable: repeat online transaction intention. These results were consistent with past findings in the literature

[12] More information on the survey administration and sampling frame is available from authors upon request.

(Fang et al., 2014; Qureshi et al., 2009; Zhou, 2013), as well as the result obtained with PEEIM in the Study 1. In Model-3, we introduced the nonlinear effects of trust. We found the β for the nonlinear effect of trust to be negative and significant (β= -0.09*), supporting our premise that trust exhibits a nonlinear effect on repeat online transaction intention. Furthermore, as illustrated in Model-4, the moderating effect of PEEIM was significant on the linear (i.e., β for PEEIM*Trust) and nonlinear effect of trust (i.e., β for PEEIM* $Trust^2$). These effects were respectively -0.17** and -0.29***, confirming a significant moderating effect on the nonlinear relationship. The nonlinear interaction effects have been presented in Figure F1 in Appendix F. It is interesting to note that interaction effects seem stronger in the e-commerce environment (Study 2) compared to that in the mobile banking environment (Study 1).

DISCUSSION

Major Findings

This research investigates the nonlinear effect of trust on repeat online transaction intention in two different perceptual conditions of institutional contexts (high and low). Results confirm that trust exhibits nonlinear effects on repeat online transaction intention in the repurchase stage, which is consistent with the extant trust literature. We are also able to detect the complex moderating effect of trust in institutional contexts on the nonlinear effect between trust in vendor and repeat online transaction intention, revealing different patterns in the two perceptual domains. In the analysis, we included several important control variables such as risk, gender, age, income, and expertise/experience. Due to this step-wise approach, we are able to witness the change of their influence and the change in their explanatory power. Hereafter, the limitations and directions for future research are presented, followed by the theoretical, practical, and methodological implications.

Limitations and Future Research

It is arguably believed that the institutional contexts in developed countries are generally better established than those in underdeveloped or developing countries (Clemons et al., 2016). Trust in institutional contexts in developed countries is therefore presumed to be relatively high. Our data, which were collected in United Kingdom and New Zealand (arguably developed countries), demonstrates this may not be the case – meaning that perceptual differences could also exist in well-developed institutional contexts. Future studies could replicate this research in other developed and less-developed countries for validation. We also detect a stronger interaction effect in the e-commerce context than it in the mobile banking context. Future research can validate this in other contexts and explore the contextual differences.

In our study, we did not collect information about other institutional environment factors. However, researchers interested in cross-country studies may include factors such as country-level technology readiness, level of IT infrastructure, etc. In future research design, researchers can also consider other parties of social influence, for example, parents/guardians for millennials' use of mobile banking.

This research employs the survey method to measure customer perceptions. Based on the findings, future research could consider designing experiments on how to manipulate the perceived effectiveness of customer trust in institutional contexts. Archival data of customers' actual buying behaviors could also be a useful addition for method triangulation.

Theoretical Implications

After two decades of development in trust research, the field is calling for research that examines the nuanced boundary condition of trust (Gefen et al., 2008; McKnight et al., 2014; McKnight et al., 2020). This research responds to this call, and to the best of our knowledge, is the first to systematically investigate the nonlinear and conditional effects of trust in repurchase with a new theoretical foundation and makes the following significant contributions.

First, drawing on Lewicki and colleagues' seminal work on stages of trust (Lewicki & Bunker, 1996; Lewicki et al., 2006), this research systematically theorizes, differentiates, and summarizes customers' trust concerns about the vendor and the environment in the initial and repurchase stages. This enriched understanding is of great value, especially when the applications of e-commerce have progressed to the repurchase stage. Similar efforts have been witnessed when scholars contribute to refining the boundary of the mature trust research (Lankton et al., 2016; McKnight et al., 2020). Second, this research goes beyond the simple belief on the nonlinear effect of trust in repurchase (Liu & Goodhue, 2012; Van der Heijden et al., 2003) and further investigates the conditional effect of such nonlinear effect, responding to the call for studying the boundary condition of trust (Gefen et al., 2008) and extending the stream of research in the repurchase stage. Third, this research formalizes the new moderating role of trust in institutional contexts in repurchase and theorizes its new function (framing the situation and interpreting trust in vendor), compared to its former antecedent role in trust-building in initial purchase (McKnight & Chervany, 2006; McKnight et al., 2002; Pavlou & Gefen, 2004). This updated understanding is important because the interactions between trust in vendor and trust in institutional contexts have been fundamentally changed in the repurchase stage. It provides new implications on how to interpret and predict the vendor's behavior when customers are knowledgeable about the vendor while still uncertain about the everchanging online and mobile transaction environment in repurchase (Kim et al., 2009b; Siau & Shen, 2003). Fourth, this research fundamentally challenges the existing theoretical foundation and draws on a new one of prospect theory, to systematically theorize how customers frame the institutional contexts in transaction decisions and how they evaluate the decisions considering intangible social elements; a perspective which has been neglected in the extant studies on repurchase that have been mostly based on social exchange theory. By doing so, (1) this research theorizes the fundamental differences between these two theoretical foundations (Table 2), thus enriching the understanding of both theories, and customer behaviors in relation to trust in the initial purchase and repurchase stages. (2) It is also able to reconcile the inconclusive findings about the moderating effect of trust in institutional contexts in the extant research (Chen et al., 2015; Fang et al., 2014; Gefen & Pavlou, 2012) and successfully validates the complex nonlinear and moderating effects in a systematic framework. (3) It also suggests two distinct conditions where trust changes in different patterns, responding to the call for studying how trust changes in the boundary and adds to the understanding in the repurchase stage beyond the existing one in initial purchase (McKnight et al., 2020).

We also advance IS research on nonlinearity studies and the applications of prospect theory. Nonlinearity studies are receiving increasing attention in IS research (Chatterjee, Moody, Lowry, Chakraborty, & Hardin, 2021; Ho, Tian, Wu, & Xu, 2017). Prospect theory is amongst the most popular frameworks for theorizing the nonlinear and conditional effects (Benlian, 2013; Brown, Venkatesh, & Goyal, 2012; Lankton et al., 2016; Venkatesh & Goyal, 2010). Our study goes beyond discussing the differential effects of positive and negative effects and applies the theory in full by explaining an individual's decision-making process on framing and value assessment, which could be valuable to future research.

This research can be also of reference value for the following. First, it showcases how to motivate research using a problematization approach (Alvesson & Sandberg, 2011) by deeply theorizing and challenging the existing underlying assumptions and justifying the new theoretical foundation for alternative explanations, responding to the discussion between problematization and gap-spotting approaches in a recent editorial (Chatterjee & Davison, 2021). Second, it illustrates how to discuss the boundary condition and examine the contributions of a theory following (Weber, 2012) (see Appendix H for details). Third, it demonstrates how to theorize and test the U- and inverted U-shaped relationships following the guide of (Haans et al., 2016) (as also discussed below in methodological implications).

Practical Implications

In this research, we point out the important perceptual role of institutional contexts. Vendors should bear this in mind when working on trust-improvement activities. By outlining how trust changes in the high and low conditions of institutional contexts, our findings suggest two precise ranges for vendors to optimize their impact on customer repeat online transaction intention (see Figure 4). Previous studies have suggested that, in a high condition of trust in institutional contexts, management should withhold trust-building resources given the diminishing effect of this expenditure over time. We recommend, however, that vendors could still dedicate resources to trust building to solidify customer trust in them before the tipping point is reached (Quadrant 3), based on the findings that trust changes at a decreasing rate in the high condition of trust in institutional contexts. Once this tipping point is achieved (Quadrant 4), the vendors could shift their resources to provide satisfactory services and enhance the functionality of website/apps, which are found to be important in repurchase decisions (Fang et al., 2014; Gefen, Karahanna, & Straub, 2003a; Khalifa & Liu, 2007; Kim, Xu, & Koh, 2004).

Based on the diminishing effect of trust, existing studies have largely ignored the condition wherein trust in institutional contexts is low in the repurchase stage. Our empirical evidence suggests vendors should be aware of this and keep up their trust-building work until Quadrant 2 (Kumar et al., 2019). To cope with low trust in institutional contexts (Quadrant 1), for example, vendors could consider highlighting their long tradition and extensive networks used to wholly support customers in the long run. Some online vendors such as Amazon have developed offline networks to reinforce their presence and cultivate ecosystem loyalty. Banks are also advised to keep their physical presence for its role in trust and credibility building (McKinsey&Company, 2017). Vendors could also pay attention to message framing. Based on our findings, negative framing of the institutional contexts could work even better because it triggers customer concerns on losses and hence encourages them to retain the relationship at an increasing rate.

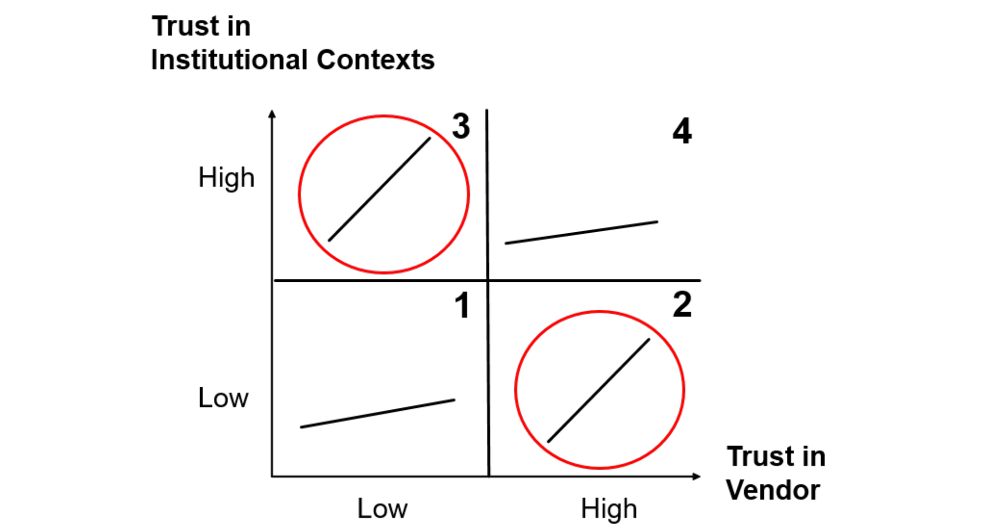

Figure 4. Illustration of Valid Operational Boundary in This Research

Methodological Implications

Complex nonlinear and moderating relationships are receiving increasing attention in IS studies since they provide a nuanced understanding of boundary conditions (Lankton et al., 2016; Lowry, Moody, & Chatterjee, 2017; Lowry et al., 2019). First, this research contributes to these debates by demonstrating how to systematically theorize and test nonlinear and conditional effects, following a rigorous guide by Haans et al. (2016). Second, the multi-study design involving different samples, contexts, and measures enhance the robustness of the results and set up a good practice. Third, this research also addresses the methodological issues associated with nonlinear latent interaction effects by implementing a latent moderated structural equations (LMS) approach – an advanced technique developed by Moosbrugger and other researchers in a series of studies (Dimitruk et al., 2007; Klein & Moosbrugger, 2000; Klein et al., 1997; Klein & Muthén, 2007; Klein & Stoolmiller, 2003; Moosbrugger et al., 1997; Schermelleh-Engel et al., 1998; Schermelleh-Engel et al., 2010). This research is one of the early efforts to apply LMS in the IS research domain. Various simulation studies have established relative accuracy and consistency of this technique compared to other usual estimation techniques such as PLS-PI (Chin et al., 2003) and CBSEM-LI (Kenny & Judd, 1984). In this paper, we provide a detailed account of the LMS technique. We elaborate on the issue of reliability and multicollinearity conundrum in latent interaction (product indicator) approaches and demonstrate how LMS approach help resolve this conundrum (Appendix G). We believe that introducing the LMS approach to the IS research domain constitutes an important methodological contribution because it increases the repertoire of tools that are available to IS scholars to better examine and understand the complex, nonlinear relationships that are increasingly observed in the IS research field.

CONCLUDING REMARKS

This research has shed light on the role of institutional contexts to investigate the nonlinear and conditional effects of trust in the repurchase stage. Drawing on prospect theory, we are able to explain customer decision-making processes and valuation considerations in the repurchase stage. We also find that trust changes differently in the two perceptual conditions of institutional contexts – high and low in trust in institutional contexts. To test the complex nonlinear and conditional effects, we introduce an advanced latent moderated structural equations (LMS) approach, thus enriching and expanding the method repertoire of the IS research community. Our findings on the two precise ranges also proffers valuable practical implications.

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APPENDICES

Appendix A. Study 1 - Construct Items and Loadings

Trust in Bank (1 = strongly disagree, 7 = strongly agree) (Einwiller, 2003; Fang et al., 2014; Garbarino & Lee, 2003; Jarvenpaa, Tractinsky, & Vitale, 2000)	
I believe that this bank …	Loading
…is consistent in quality and service.	0.81
…is keen on fulfilling my needs and wants.	0.79
…is honest.	0.84
…is one that keeps promises and commitments.	0.85
…has my best interests in mind.	0.80
…is trustworthy.	0.87
…has high integrity.	0.87
…is dependable.	0.84
Structural Assurance (1 = strongly disagree, 7 = strongly agree) (McKnight, Choudhury, & Kacmar, 2002)	
M-banking has enough safeguards to make me feel comfortable to continue to use it for personal financial transactions.	0.90
I will continue to use m-banking as I feel assured that legal and technological structures adequately protect me from m-banking problems.	0.89
I feel confident that encryption and other technological advances associated with m-banking make it safe for me to continue to conduct personal financial transactions.	0.87
In general, m-banking is now a robust and safe environment for me to continue to conduct personal financial transactions.	0.86
Perceived Effectiveness of E-Commerce Institutional Mechanisms (1 = strongly disagree, 7 = strongly agree) (Fang et al., 2014)	
I am confident that there are mechanisms in place to protect me against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.74
I have faith in third parties (e.g., CellTrust; VeriSign) to enforce the m-banking guarantee provided by my financial institution against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.77
I believe that the regulatory body (e.g., the Financial Conduct Authority) has an obligation to protect me against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.84
I am sure that I cannot be taken advantage of (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.72
Repeat Online Transaction Intention (Fang et al., 2014; Jarvenpaa et al., 2000)	
How likely is it that you will continue to stay with this bank and keep using their m-banking application to conduct personal financial transactions? (1 = very unlikely, 7 = very likely)	

…in the medium term.	0.65
…in the long term.	0.88
All things considered, and on a scale of 0-100%, what is the probability that you will stay with this bank and keep using their m-banking application to conduct personal financial transactions?	0.83
Control variables	
Risk All things considered, and on a scale of 0-100%, what is the probability that something could go wrong when conducting m-banking for personal financial transactions?	
M-banking Experience How long have you been using this bank's m-banking facility? Please tick: Up to 6 months 7 to 12 months 13 to 18 months 19 to 24 months More than 24 months	

Appendix B. Study 1 - Correlations, Reliability, and Square Root of AVE

	ICR[a]	ROTI	SA	PEEIM	TB	R	MB	G	A
Repeat Online Transaction Intention (ROTI)	.83	***.79***[b]							
Structural Assurance (SA)	.93	.54***	***.88***						
Perceived Effectiveness of E-Commerce Institutional Mechanisms (PEEIM)	.85	.42***	.64***	***.77***					
Trust in Bank (TB)	.95	.60***	.61***	.53***	***.83***				
Risk (R)	na	-.11*	-.25***	-.34***	-.14**	--			
M-banking Experience (MB)	na	.13**	.21***	.19***	.11*	-.09*	--		
Gender (G)	na	.08	.05	-.01	.08	.22***	-.06	--	
Age (A)	na	-.05	-.06	.03	-.02	-.00	.11*	.01	--
Income (I)	na	-.07	-.11*	-.07	-.06	-.02	.03	-.03	.19***

[a]: ICR - Internal Consistency Reliability. Not applicable for single item constructs.
[b]: Diagonal elements (bold and italic) represent square root of the AVE; not applicable for single item constructs.
***p<0.001, ** p<0.01; *p<0.05.
The two items of ROTI were measured on Likert scale and one item was measured on a continuous scale of 0-100. These three items were standardized before using them in measurement model, where ROTI had mean=0 and standard deviation=1; mean and standard deviation for SA were respectively 5.31 and 1.14, for PEEIM respectively 5.13 and 1.19, and those for TB were 5.45 and 1.13.

Appendix C. Study 1 - Replication Analysis Using PEEIM as Moderator

Table C1. Results of Nested Structural Equations Models				
	Model-1	**Model-2**	**Model-3**	**Model-4**
Control Variables				
--Risk	-0.00	0.00	0.00	0.00
--M-banking Experience	0.06^{*}	0.03	0.03	0.02
--Gender	0.11	0.07	0.07	0.06
--Age	-0.07^{+}	-0.04	-0.04	-0.03
--Income	-0.02	-0.01	-0.01	-0.01
Trust in Bank (Trust) (β1)		0.35^{***}	0.33^{***}	0.30^{***}
PEEIM (β5)		0.14^{**}	0.13^{**}	0.13^{**}
$Trust^2$ (β2)			-0.15^{*}	-0.12^{*}
PEEIM*Trust (β3)				-0.09^{*}
PEEIM* $Trust^2$ (β4)				-0.13^{*}
Fit indices				
χ^2 (df)	19.96 (9)	304.70 (154)		
CFI	.980	.967		
TLI	.960	.961		
RMSEA	.052	.047		
SRMR	.023	.041		
AIC	3260.16	20235.72	20225.47	20201.54
BIC	3321.60	20510.14	20504.99	20492.25
SABIC	3273.99	20297.51	20288.19	20267.10
Free parameters	15	67	68	70
H_0-value	-1615.08	-10050.86	-10043.74	-10026.27
H_0- Scaling Correction Factor for MLR			1.4218	1.4765
$\Delta\chi^2$ using correction factor				10.473
p-value ($\Delta\chi^2$)				0.005
Turning point (β1*β4 - β2*β3) move to the left as PEEIM increases				-0.023
Flipping point (- β2/ β4)				-0.923
Note: Nonlinear and interaction effects were estimated using LMS ***p<0.001, **p <0.01; *p <0.05; +<0.1; Steepening of inverted U shape as β2 and β4 both are negative. R^2 (Model 1) = 0.049; R^2 (Model 2) = 0.306; R^2 (Model 3) = 0.355.				

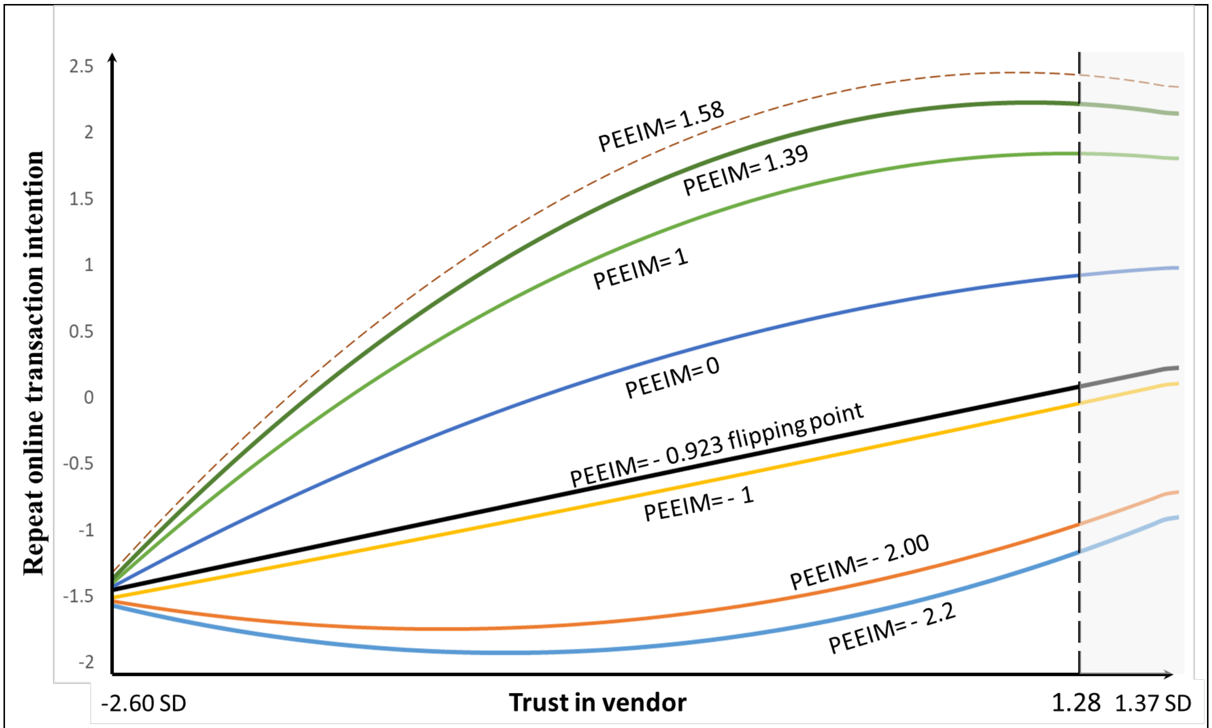

Figure C1. Nonlinear Interaction Effects

(Note: μ=0, and SD=1 for all the latent variables used in this figure. Consistent with Haans et al. (2016) recommendations, the possible and observed range of variables have been used in the Figure. For trust in vendor 1.37 SD was possible upper limit of the variable but the highest observed value was 1.28 SD. Similarly, for PEEIM 1.58 SD was possible upper limit of the variable but the highest observed value was 1.39 SD)

Appendix D. Study 2 - Construct Items and Loadings

Trust in Bank (1 = strongly disagree, 7 = strongly agree) (Einwiller, 2003; Fang et al., 2014; Garbarino & Lee, 2003; Jarvenpaa et al., 2000)	
I believe that this vendor …	Loading
…is consistent in quality and service.	0.70
…is keen on fulfilling my needs and wants.	0.71
…is honest.	0.81
…is one that keeps promises and commitments.	0.72
…has my best interests in mind.	0.74
…is trustworthy.	0.87
…has high integrity.	0.89
…is dependable.	0.92
Perceived Effectiveness of E-Commerce Institutional Mechanisms (1 = strongly disagree, 7 = strongly agree) (Fang et al., 2014)	
I am confident that there are mechanisms in place to protect me against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.74
I have faith in third parties (e.g., CellTrust; VeriSign) to enforce the m-banking guarantee provided by my financial institution against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.71
I believe that the regulatory body (e.g., the Financial Conduct Authority) has an obligation to protect me against any potential risks (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.69
I am sure that I cannot be taken advantage of (e.g., leaking of financial data, security breaches, financial fraud, financial instructions not/incorrectly carried out) if something goes wrong	0.72
Repeat Online Transaction Intention (Fang et al., 2014; Jarvenpaa et al., 2000)	
Please indicate the degree to which you agree with the following statements concerning your likelihood/probability of buying online again from the vendor you had in mind as you filled out this questionnaire	
…in the medium term. (1-Strongly disagree, 7- Strongly agree)	0.88
…in the long term. (1-Strongly disagree, 7- Strongly agree)	0.88
All things considered, and on a scale from 1-100%, what is the probability that you will purchase online from the same vendor again? __________%	0.89
Control variables	
Risk (Jarvenpaa, Tractinsky, & Saarinen, 1999) (1-Strongly disagree, 7- Strongly agree)	
Compared with other ways of shopping there is more risk involved in buying goods or services via the Internet	.91
Compared with other ways of shopping there is a higher potential for loss when buying goods or services via the Internet.	.88
Compared with other ways of shopping there is more uncertainty associated with buying goods or services via the Internet.	.89

There is no more risk involved in buying goods or services via the Internet than there is by buying goods or services via other means (high street shops etc.)	.87
Expertise (Jamal & Naser, 2002) (1-Strongly disagree–7 Strongly agree)	
I know a lot about conducting purchases via the Internet	.89
I am experienced in conducting purchases via the Internet	.92
I am informed about conducting purchases via the Internet	.88
I am an expert buyer of products/services via the Internet	.90

Appendix E. Study 2 - Correlations, Reliability, and Square Root of AVE

	ICR[a]	ROTI	PEEIM	TV	R	EXP	G	A
Repeat Online Transaction Intention (ROTI)	.91	***.88***[b]						
Perceived Effectiveness of E-Commerce Institutional Mechanisms (PEEIM)	.81	.31***	***.72***					
Trust in Vendor (TV)	.93	.21***	.17**	***.80***				
Risk (R)	.94	-.02	-.15*	-.17***	***.89***			
Expertise in online transaction (EXP)	.94	.02	.16*	.03	-.7	***.90***		
Gender (G)	na	.01	.05	.02	.00	-.05	--	
Age (A)	na	-.05	-.15*	.06	-.11*	.01	.02	--
Income (I)	na	-.04	-.04	-.07	-.02	.13*	-.12*	.18***

[a]: ICR - Internal Consistency Reliability. Not applicable for single item constructs.
[b]: Diagonal elements (bold and italic) represent square root of the AVE; not applicable for single item constructs.
***p<0.001, ** p<0.01; *p<0.05.
The two items of ROTI were measured on Likert scale and one item was measured on a continuous scale of 0-100. These three items were standardized before using them in measurement model, where ROTI had mean=0 and standard deviation=1; mean and standard deviation for PEEIM were respectively 5.26 and 1.25, and those for TB were 4.62 and 1.09.

Appendix F. Study 2 – Structural Model

Table F1. Results of Nested Structural Equations Models				
	Model-1	**Model-2**	**Model-3**	**Model-4**
Control Variables				
--Risk (four items scale)	0.02	0.03	0.02	0.03
--expertise (four items scale)	0.01	0.02	0.02	0.02
--Gender	0.01	0.03	0.03	0.02
--Age	0.00	0.00	0.00	0.00
--Income	-0.01	-0.01	-0.01	0.01
Trust in Vendor (Trust) (β1)		0.34^{***}	0.27^{**}	0.25^{**}
PEEIM (β5)		0.08^{*}	0.08^{*}	0.07^{*}
$Trust^2$ (β2)			-0.09^{*}	-0.08^{*}
PEEIM*Trust (β3)				-0.17^{**}
PEEIM* $Trust^2$ (β4)				-0.29^{***}
Fit indices				
χ^2 (df)	121.04 (69)	424.49 (275)		
CFI	.993	.986		
TLI	.991	.983		
RMSEA	.044	.038		
SRMR	.053	.047		
AIC	6810.74	16906.78	16901.54	16837.96
BIC	6988.41	17289.74	17283.45	17232.76
SABIC	6845.63	16981.97	16972.51	16915.48
Free parameters	45	97	98	100
H_0-value	-3360.37	-8356.39	-8351.27	-8316.98
H_0- Scaling Correction Factor for MLR			1.7094	1.7550
$\Delta\chi^2$ using correction factor				17.191
p-value ($\Delta\chi^2$)				0.0002
Turning point (β1*β4 - β2*β3) move to the left as PEEIM increases				-0.0086
Flipping point (- β2/ β4)				-0.276
Note: Nonlinear and interaction effects were estimated using LMS ***p<0.001, **p <0.01; *p <0.05; +<0.1; Steepening of inverted U shape as β2 and β4 both are negative. R^2 (Model 1) = 0.007; R^2 (Model 2) = 0.112; R^2 (Model 3) = 0.151				

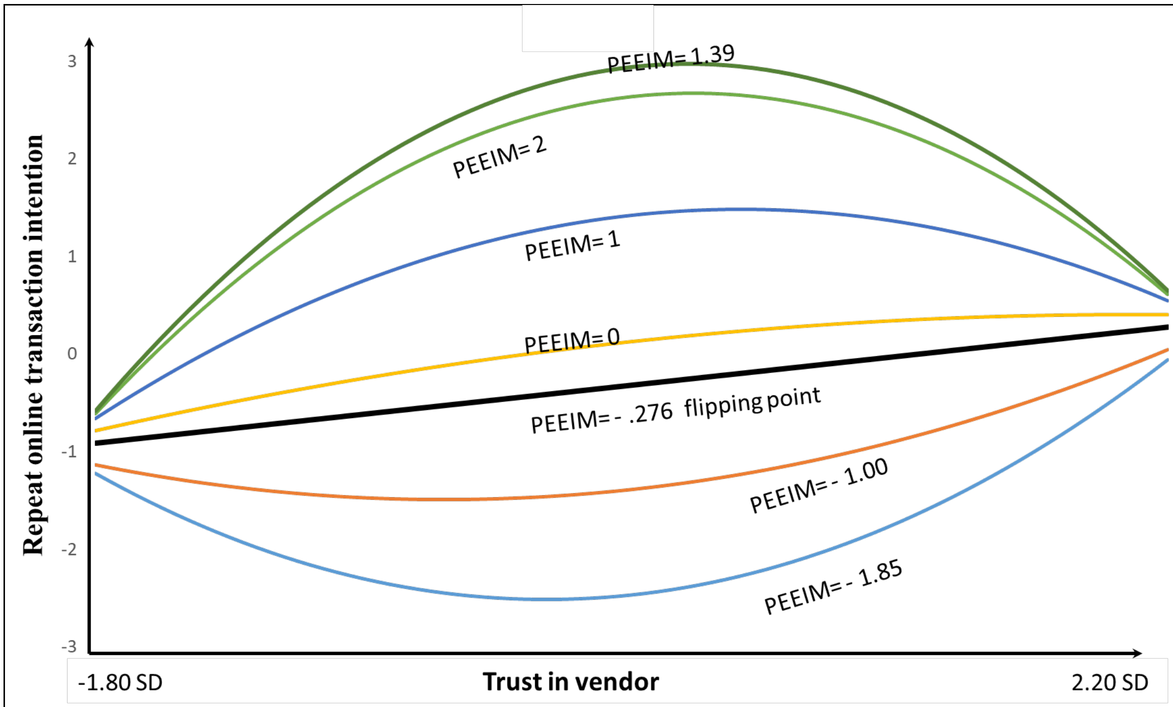

Figure F1. Nonlinear Interaction Effects

(Note: μ=0, and SD=1 for all the latent variables used in this figure. Consistent with Haans et al. (2016) recommendations, the possible and observed range of variables have been used in the Figure. For trust in vendor 2.20 SD was possible upper limit which was also observed. Similarly, for PEEIM 1.39 SD was possible upper limit of the variable and was also observed.

Appendix G. Conundrum of Reliability and Multicollinearity in Product Indicator Based Approaches

In order to appreciate the advancements and benefits of Latent Moderated Structural Equations (LMS) approach, it is important to understand the conceptual basis for LMS
Typically, interaction and nonlinear effects are conceptualized through equation A

$$Y = \alpha + \beta_1 X + \beta_2 Z + \gamma_{12} XZ + \gamma_{11} X^2 + \gamma_{22} Z^2 + \varepsilon \qquad \text{-------------- } (A)$$

where α is the intercept of the regression equation, β_1 and β_2 are the main effects of X and Z, respectively, γ_{12} is the interaction effect of XZ, γ_{11} is the quadratic effect of X, and γ_{22} is the quadratic effect of Z, and ε is the residual of the regression equation.

LMS uses the following general form to represent interactions and nonlinear effects (Klein & Moosbrugger, 2000, see also Klein & Muthén, 2007), and utilizes heteroscasdacity in the estimation of nonlinear effects (Klein & Moosbrugger, 2000; Klein & Muthén, 2007; Schermelleh-Engel, Klein, & Moosbrugger, 1998).[13]

$$\eta = \alpha + \Gamma\xi + \xi`\Omega\,\xi + \zeta \qquad \text{------------------------ } (B)$$

where η is the latent endogenous variable, α is the intercept, ξ are the latent exogenous variables, Γ are the main effects of ξ on η, Ω are the nonlinear effects of ξ on η, and ζ is the residual of η.

Therefore, equation A can be expressed as follows (Kelava et al., 2011)

$$Y = \alpha + (\beta 1 \;\; \beta 2).\begin{pmatrix} X \\ Z \end{pmatrix} + (X \;\; Z).\begin{pmatrix} \gamma 11 & \gamma 12 \\ 0 & \gamma 22 \end{pmatrix}.\begin{pmatrix} X \\ Z \end{pmatrix} + \zeta \qquad \text{------------- } (C)$$

It is important to note that the latent interaction (LI or product indicators-PI) approach (Kenny & Judd, 1984) and its variants, including PLS-PI, treat the interaction term XZ and the quadratic terms X^2 and Z^2 in equation *A* as latent variables and therefore requires the creation of product indicators to represent ("measure") these latent variables. On the other hand, equation *C* shows that LMS uses matrix multiplication of X and Z to estimate the interaction and quadratic effects on Y without creating latent variables to represent the product term XZ and quadratic terms X^2 and Z^2 in the estimation model. Thus, LMS does not require the creation of product indicators to represent the latent interaction and quadratic terms, which avoids the need to impose complicated

[13] The discussion of exact estimation steps is beyond the scope of this Appendix. The interested readers are advised to read seminal papers on LMS approach (Klein & Moosbrugger, 2000; Schermelleh-Engel et al., 1998).

nonlinear constraints. This differentiates LMS, contrasting with PI which uses product indicators and nonlinear constraints.

The implications of this estimation process are several, but we will discuss the two most important and relevant for our research.

a) Multicollinearity - The problem of multicollinearity is exacerbated in nonlinear models that include interactions or quadratic effects. SEM analyses with nonlinear effects are affected by multicollinearity due to correlations: i) among the predictor latent variables, ii) between predictor latent variables and the higher-order terms (interactions and quadratic effects), and iii) among various higher-order terms.

   Multicollinearity primarily results in parameter estimates with inflated standard errors and decreased power in detecting "true" effects. This problem is heightened in nonlinear latent models due to reliability issues associated with indicators of higher terms, an issue that we will return to. When multicollinearity between the independent latent variables and nonlinear terms is present, the observed interaction or quadratic effect may be spurious. In this case, the coefficient of the nonlinear term in the model may be significant even when there is no interaction or no quadratic effects (Ganzach, 1997; Kelava, Moosbrugger, Dimitruk, & Schermelleh-Engel, 2008). For example, as the correlation between X and Z increases, correlations between XZ and X^2, between XZ and Z^2, and between X^2 and Z^2 increase in parallel. This results in an overlap between the variance explained by XZ and the variance explained by X^2 or Z^2 (cf. Busemeyer & Jones, 1983). This multicollinearity in the higher-order terms remains even after the centering (or standardization) is performed before creating higher-order terms.

   Kelava and colleagues (2008) present an illustration of this. Assume X and Z to be bivariate normally distributed and centered. If X and Y have a correlation of 0.50, then X^2 and Z^2 will correlate at 0.25, X^2 and XY will correlate at 0.63, and Y^2 and XY will correlate at 0.63 (see Bohrnstedt and Goldberger (1969) for conceptual insights, and Dimitruk, Schermelleh-Engel, Kelava, and Moosbrugger (2007) for further elaboration).

   In contrast to product indicators approaches (Kenny & Judd, 1984), LMS does not use products of indicators as indicators of latent nonlinear terms in the measurement model. Instead, LMS applies the EM algorithm (Dempster, Laird, & Rubin, 1977) to obtain ML estimates of the parameters (Klein & Muthen, 2007),[14] and these parameters are based on the analysis of the multivariate distribution of the joint indicator vector (Klein & Moosbrugger, 2000). Thus, the multicollinearity issues associated with nonlinear effects, as discussed above, do not present multicollinearity threats in LMS (Kelava et al., 2008).

[14] The joint distribution of the indicator variables is thereby represented as a finite mixture of normal distributions. The discussion of finite mixture of normal distribution is beyond the scope of this Appendix. But suffice to mention that LMS has been explicitly designed to deal with the nonnormality of the latent interaction term by accounting for its distribution (Klein & Moosbrugger, 2000)

b) Reliability - The reliability problem – or measurement errors (Zwanenburg & Qureshi, 2019) can lead to biased estimates. This issue is further amplified when nonlinear terms are added (Aguinis, 1995; Kelava et al., 2008), as the reliabilities of nonlinear terms are affected to an extent where coefficients associated with these terms vastly underestimate the population coefficients. This problem can further get amplified if the reliability of the endogenous latent variable, i.e., the dependent latent variable, Y, is also less than perfectly measured. Thus, the relationships between Y and the predictor latent variables (e.g., X, Z, XZ, X^2, Z^2) are attenuated even more (Dimitruk et al., 2007; Kelava et al., 2008).

Equation D provides the relationship between the reliability of the interaction term (XZ)[15] and the respective reliabilities of X and Z (Busemeyer & Jones, 1993; Dimitruk et al., 2007), assuming X and Z are centered

$$\mathrm{Rel}(XZ) = \frac{\mathrm{Rel}(X).\mathrm{Rel}(Y) + [\mathrm{Corr}(X,Z)]^2}{1 + [\mathrm{Corr}(X,Z)]^2} \quad \text{-----------} (D)$$

where Rel(XZ) is the reliability of the interaction term, Rel(X) is the reliability of predictor X, Rel(Z) is the reliability of moderator Z, and Corr(X,Z) is correlation between X and Z.

For quadratic terms, i.e., X^2 and Z2, the respective reliabilities are expressed as:

$$\mathrm{Rel}(X^2) = [\mathrm{Rel}(X)]^2 \quad \text{-----------} (E)$$

$$\mathrm{Rel}(Y^2) = [\mathrm{Rel}(Y)]^2 \quad \text{-----------} (F)$$

Equation D indicates that the reliability of the interaction term depends not only on reliabilities of X and Y but also on the correlation among them. Thus, even when both X and Z are measured with reasonable reliability (e.g., 0.7) then at zero correlations between X and Z, the reliability of interaction term XZ will be 0.49, much lower than X and Z. However, for the given reliabilities of X and Z, the reliability of XZ increases, as correlations between X and Z increases. Thus, when X and Z have a reliability of 0.7 and correlation between X and Z is 0.7, the interaction term XZ has a reliability of 0.66.[16] This results in a conundrum. In product indicator based approaches, a higher correlation among predictor and moderator latent variables is desirable for reliability of interaction term, but it is undesirable from the perspective of multicollinearity (as discussed above). This conundrum is labeled as the problem of "interdependency of multicollinearity and reliability" (Kelava et al., 2008, p. 62) for nonlinear terms. Product indicators approaches (Kenny & Judd, 1984) and its variants, including PLS-PI, cannot overcome this conundrum.

[15] Generally researchers do not pay attention to reliability issues related to interaction or other higher order terms; however poor reliabilities can reflect in parameter estimation and poor fit indices.
[16] As equation E and F shows, the reliabilities of X^2 and Y^2, in this case, will be 0.49.

This conundrum doesn’t exist in LMS because it does not use indicators for the nonlinear terms, as problems “concerning reliability differences of indicators across constructs (or nonlinear latent predictors) or even underspecifications of measurement error covariances cannot arise in the LMS approach” (Kelava et al., 2008, p 63). This is an important distinguishing feature of LMS, and hence its application in this research.

Appendix H. Evaluating and Developing IS Theories using Weber's (2012) Approach

Let's take Weber's (2012) guide as an example of examining the contributions of our research.

According to Weber's (2012), all theories have three parts, namely constructs, associations, and states. For a theory that covers dynamic phenomena, it contains the fourth part, events. To clearly define a boundary condition of a theory and make contributions to the theory, these parts need to be clearly defined.

In the event space of e-commerce in our research, new events have been observed, such as a progression to the repurchase stage and new technologies available in the environment. These events change the states. For example, customers' trust in vendor and trust in institutional contexts have been updated; customers' trust concerns in the initial purchase (calculus-based trust) and repurchase stage (knowledge-based trust) have also changed.

Several constructs are involved, such as trust in vendor, trust in institutional contexts, structural assurance and perceived effectiveness of e-commerce institutional mechanisms (as instances of vendor-independent institutional contexts), and repeat online transaction intention (clearly defined in the repurchase stage).

In the dynamic phenomena this research addresses in the new repurchase stage, constructs are associated with each other in a new and more dynamic way: The effect between trust in vendor and repeat online transaction intention has changed from linear to nonlinear; The effect between trust in vendor and trust in institutional contexts has changed from linear to interactional.

By clearly defining these four parts, we are able to capture the status quo of the existing theory and propose how our new theory can refine the boundary condition based on it. To examine the new theory we propose, five criteria can be applied to assess the "whole": importance, novelty, parsimony, level, and falsifiability. Table H1 summarizes the examination of our research applying these criteria.

Table H1. Examination of the Parts and Whole
(adapted from (Lowry et al., 2019; Weber, 2012))

Event space: e-commerce	
Parts	
Events	Clearly defined in the motivation.
States	Clearly theorized in Table 1.
Constructs	Clearly clarified and justified.
Associations	Clearly reviewed and theorized.
Whole	
Importance	Important given the progression to the repurchase stage.
Novelty	The new theoretical foundation brings a novel perspective.
Parsimony	Parsimonious as it only covers the principal constructs.
Level	Appropriate as a middle-range theory.
Falsifiability	Falsifiable for the testable operationalization. Also received robust support from the empirical results.

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