

2010

The Asymmetric Effects of Trust and Distrust: An Empirical Investigation in a Deception Detection Context

Bo Xiao

Hong Kong Baptist University, boxiao@comp.hkbu.edu.hk

Izak Benbasat

The University of British Columbia, izak.benbasat@sauder.ubc.ca

Follow this and additional works at: <http://aisel.aisnet.org/sighci2010>

Recommended Citation

Xiao, Bo and Benbasat, Izak, "The Asymmetric Effects of Trust and Distrust: An Empirical Investigation in a Deception Detection Context" (2010). *SIGHCI 2010 Proceedings*. 20.

<http://aisel.aisnet.org/sighci2010/20>

This material is brought to you by the Special Interest Group on Human-Computer Interaction at AIS Electronic Library (AISeL). It has been accepted for inclusion in SIGHCI 2010 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

The Asymmetric Effects of Trust and Distrust: An Empirical Investigation in a Deception Detection Context

Bo Xiao

Department of Computer Science
Hong Kong Baptist University
boxiao@comp.hkbu.edu.hk

Izak Benbasat

Sauder School of Business
The University of British Columbia
izak.benbasat@sauder.ubc.ca

ABSTRACT

The academic research community's interest in studying online fraud and deception has not been high. This study fills this gap by focusing on deceptive online product recommendation agents (PRAs) and empirically examining the dynamics of trust and distrust relationships in the context of detecting such a novel form of deception. The results indicate that trust and distrust are distinct and are both indispensable concepts in a deception detection context. More importantly, trust and distrust have asymmetric effects on consumers' intention to use the PRA moderated by the level of risk embedded in a particular situation. This study not only contributes to theory building in trust and distrust but also has practical implications for online vendors.

Keywords

Trust, Risk, Deception, Online Product Recommendation Agents, Electronic Commerce

INTRODUCTION

The rapid growth of electronic commerce (e-commerce) has created fertile ground for online fraud and spawned novel forms of deceptive practices (Roman, 2010; Grazioli and Jarvenpaa, 2000). This paper focuses on deception by online product recommendation agents (PRAs), which are software artifacts that take as input individual consumers' product-related preferences and subsequently provide recommendations for products that match the consumers' expressed interests or preferences (Xiao and Benbasat, 2007). Appropriately designed PRAs enable consumers to make informed purchase decisions by reducing their decision effort while improving their decision quality. However, unscrupulous online companies can take advantage of consumers by designing PRAs that provide recommendations biased toward the companies' own interests.

Surprisingly, there is a paucity of empirical research effort directed to this phenomenon (exceptions include Xiao, 2010). This study fills this gap by examining the dynamics of trust and distrust relationships in the context of detecting such a novel form of deception. More specifically, we test the asymmetrical influences of trust

and distrust on intentions to utilize a PRA, depending on whether or not the user has noticed any anomaly in the PRA. The implications of this study are twofold: First, in addition to demonstrating trust and distrust as distinct constructs by assessing their discriminant validity, this study goes a step further by investigating the differential effects of trust and distrust under situations of varying levels of risk. Hence, it furthers our understanding of the separate roles trust and distrust play in e-commerce contexts. Second, it has practical implications for providers of PRAs in particular and for online vendors in general. If trust and distrust manifest differential effects in different risk situations, the level of risk faced by the customers can then dictate whether online vendors should focus on managing trust or distrust. To do that, vendors are advised to identify a set of distrust antecedents (e.g., verification mechanism and third-party assurance) as well as trust antecedents (e.g., explanation, reputation mechanism, and consumer review) (Wang and Benbasat, 2008).

The remainder of this paper proceeds as follows: First we offer a review of the relevant literature. We then present our research model, develop our hypotheses, and describe our research methodology. Next we outline the results of our empirical investigation. Finally, we offer a discussion and some concluding remarks about this study.

LITERATURE REVIEW

In this part, we review relevant literature on the process of deception detection, and trust vs. distrust.

Process of Deception Detection

Individuals detect deception by identifying anomalies in the environment that has been manipulated by the deceiver and then interpreting these anomalies in the light of the deceiver's adversarial goals (Dennett, 1987; Johnson et al., 1993). The *model of deception detection* (Johnson et al., 1993; Johnson et al., 2001), describes four sub-processes by which individuals, based on their domain knowledge and the available information cues, decide if the information provided by another party is deceptive. The *activation* sub-process consists of identifying anomalies based on the presence of discrepancies between what is observed and what is

expected. Once an anomaly is identified, individuals generate potential hypotheses to explain the anomaly (the *hypothesis generation* sub-process) and evaluate the hypotheses to determine their acceptability (the *hypothesis evaluation* sub-process). Finally, individuals combine the accepted hypotheses into a final assessment of deceptiveness (the *global assessment* sub-process) (Johnson et al., 2001). Of the four sub-processes of the *model of deception detection*, the *activation* sub-process is the most critical, as it initiates the whole deception detection process and triggers subsequent interpretation processes (Johnson et al., 1993; Johnson et al., 2001).

Trust and Distrust

Trust is based on the implicit assumption that another party has respect and concern for one's welfare (Robinson, 1996). When consumers perceive that the e-commerce website fails to live up to its commitments by engaging in deceptive practices, trust is shattered as a result (Robinson, 1996; Rotter, 1967). Whereas *trust* has been established as an important link between perception of deception and later outcomes (such as behavioral intention) (Robinson, 1996; Grazioli and Jarvenpaa, 2000; Pavlou and Gefen, 2005), *distrust* has not been empirically examined in this context.

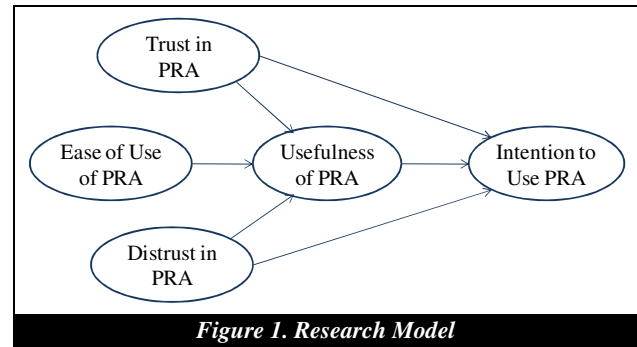
The main dispute about *trust* and *distrust* is whether they are two sides of one continuum or two distinct concepts. Traditionally, *trust* and *distrust* are viewed as existing at opposite ends of a single continuum, whereby low *trust* indicates high *distrust* (Lewicki et al., 1998). Recently, however, researchers tend to consider *trust* and *distrust* as two related but distinct concepts. For instance, Lewicki et al. (1998) argue that *trust* and *distrust* can operate simultaneously. As people become acquainted with one another, they learn to *trust* someone in one area but *distrust* him in another. McKnight and colleagues (McKnight and Choudhury, 2006; McKnight et al., 2004) further suggest that *trust* and *distrust* are based on different underlying psychological states: Whereas *trust* focuses on positive emotions such as hope, confidence, and assurance, *distrust* involves strong negative emotions such as suspicion, fear, and wariness.

However, little empirical evidence has demonstrated that *trust* and *distrust* are distinct concepts, in part because the two concepts are rarely studied together with a few exceptions. For instance, McKnight and colleagues (McKnight et al., 2004; McKnight and Choudhury, 2006) revealed that *trust* and *distrust* predict different variables, with *distrust* being an important predictor of risky actions in B2C e-commerce (e.g., share information and purchase online). Komiak, Wang, and Benbasat (Komiak et al., 2004/2005) found that the processes of trust building differ from the processes of distrust building. Cho (2006) showed that trust and distrust are shaped by different dimensions of trustworthiness and that trust affects behavior intentions differently from distrust. Dimoka (2009) found in a fMRI neuroimaging study that trust and

distrust activate different brain areas, which helps explain why *trust* and *distrust* are distinct constructs associated with different neurological processes. However, to our knowledge, no prior study has examined the differential effect of trust and distrust on the same outcome variable(s) under different risk situations.

RESEARCH MODEL AND HYPOTHESES

The research model for this study is shown in Figure 1.



Trust has been established as an important predictor of behavioral intention in online shopping (e.g., Gefen et al., 2003; Pavlou, 2003). It is particularly salient for first time PRA users who have limited understanding of the PRA's behavior (Komiak and Benbasat, 2006; Wang and Benbasat, 2005). Although research on distrust is scant, existing empirical evidence nevertheless supports its negative effect on usage intention. For instance, Cho (2006) found that distrust in an e-vendor significantly reduced consumers' intention to disclose personal information and to maintain a long-term relationship with the e-vendor. McKnight and Choudhury (2006) showed that consumers' distrust in a legal advice website significantly hampered their intention to use the website for legal help. Likewise, consumers' distrust in a PRA may motivate them to take preventive actions against the PRA's manipulations, thus leading to reduced cooperation/commitment (Luhmann, 1979). Therefore,

H1: Consumers' *trust in the PRA* will positively influence their *intention to use the PRA*.

H2: Consumers' *distrust in the PRA* will negatively influence their *intention to use the PRA*.

Trust and distrust also influence the perceived usefulness (PU) of PRAs. PU is concerned with the benefits consumers expect to achieve from using the PRAs. Trust establishes the credibility of the PRAs, thus providing a form of guarantee that the PRAs have appropriate expertise in the task domain, genuinely care about their users, and behave in an honest fashion, all of which increase the likelihood that the consumers will gain the expected benefits from using the PRAs (Gefen et al., 2003; Wang and Benbasat, 2005). In contrast, when consumers become distrustful of the PRAs, they would call into question the competence, benevolence, and integrity of the PRAs, hence will be less likely to believe that they would reap the expected benefits from using the

PRA. While ample empirical evidence (e.g., Gefen et al., 2003; Pavlou, 2003; Wang and Benbasat, 2005) supports trust as an important predictor of PU, no prior research has examined the impact of distrust on PU. Thus,

H3: Consumers' *trust in the PRA* will positively influence *perceived usefulness of the PRA*.

H4: Consumers' *distrust in the PRA* will negatively influence *perceived usefulness of the PRA*.

Despite the fact that trust and distrust can co-exist, their effects on intention to use are not necessarily *symmetrical* (Cho, 2006). McKnight and colleagues (McKnight et al., 2004; McKnight and Choudhury, 2006) propose that variations in the level of risk involved in an activity will change the competing effects of trust and distrust on the activity. When the risk is high, individuals would rely on the wary, suspicious side (i.e., distrust) to assess the consequence of engaging in the activity rather than relying on the optimistic, positive side (i.e., trust). Moreover, since distrust embodies paranoid feelings and negative emotions, it is much more salient in risk-laden situations when compared to trust (Kramer, 1999). Therefore, the impact of distrust may enhance in high-risk situations (e.g., when consumers have noticed anomalies in the PRA's recommendations) whereas the predictive power of trust may become stronger in low-risk situations (e.g., when consumers have not noticed anomalies). Thus,

H5-H6: There is an asymmetric effect of *trust* and *distrust* on *intention to use the PRA*, with *distrust* weighing more than *trust* for consumers who have *noticed anomalies* in the PRA's recommendations (**H5**) and *trust* weighing more than *distrust* for consumers who have not (**H6**).

The causal links among *PEOU*, *PU*, and *intention* have been established in the Technology Acceptance Model (TAM) (Davis, 1989). Therefore,

H7-H8: *Perceived usefulness* (**H7**) and *ease of use* (**H8**) of the PRA will positively influence consumers' *intention to use the PRA*.

RESEARCH METHOD

Participants for this study were 256 e-commerce shoppers recruited from a North American panel accessed via a marketing research firm. 56.5% of the participants were females. The majority of the participants (62.2%) were between 30-49 years old. Over 50% of the participants use Internet for at least 20 hours each week. Also, more than half of the participants made at least five purchases online during the past 12 months. The demographic profile of the participants is similar to that of online shoppers reported elsewhere (e.g., Pew-Internet, 2009).

Experimental Design

A two-group between-subject design was used, with the independent variable being *Type of PRA* (i.e., whether the PRA provided at the e-commerce website is honest or deceptive). Two experimental websites (providing a deceptive PRA and an honest one respectively) were

custom-designed for this study. Each website featured the same 96 digital cameras from 8 brands, with 12 products in each brand. The product features for the 12 digital cameras in each brand were carefully designed such that 6 products (referred to as the *promoted* products) were dominated by the other 6 products (referred to as the *dominant* products). Each *promoted* product was paired with a *dominant* product in the same brand that had better features but same price. Two PRAs for digital cameras were adapted from Wang and Benbasat (2005). Table 1 illustrates how they were designed.

Both Deceptive and Honest PRAs: After calculating a fit score for every available product based on users' expressed needs, the PRA will generate a list of 12 products, with 6 products in each page

Honest PRA: Select 12 products that have the highest fit-scores and present them in the recommendation list
--

Deceptive PRA: Select 12 products <u>in the promoted set</u> that have the highest fit-scores and present them in the recommendation list
--

Table 1. The Design of PRAs

Experimental Task and Procedures

Participants were randomly assigned to one of the two experimental groups. They were told that an online camera store was testing an automated shopping advisor implemented to assist consumers in choosing digital cameras while shopping in the store. Their task was to evaluate this shopping advisor and determine whether it was honest or deceptive.

Participants first completed a short questionnaire to collect background information. They were then asked to read task instructions and click on a "Start Shopping" button that would take them to their assigned e-commerce website. Upon completion of the evaluation task at the website, participants were asked to fill out a questionnaire that included the measures of the dependent variables.

Measurement

Most of the measurements for dependent variables were 7-point scales adapted from prior research except for the measurements of *perceived anomaly in the PRA's recommendations*, which were newly developed for this study. All the measurements were validated via several rounds of pilot testing.

RESULTS

Measurement Model

Partial Least Squares (PLS), as implemented in SmartPLS 2.0.M3, was used to assess both the measurement model and the structural model. Individual item reliability was examined by the loadings of measures with their corresponding construct (Barclay et al., 1995). Most of the loadings exceed 0.7, indicating good item reliability.

Internal consistency was assessed by examining the composite reliability index (Fornell and Larcker, 1981). All constructs met the benchmark of 0.7 for acceptable reliability. Barclay et al. (1995) suggest two criteria for discriminant validity. First, the square root of AVE of a construct should be greater than the correlations of the construct with other constructs. Second, no item should load higher on a construct other than the one it intends to measure. Both criteria are satisfied by all the measurement items.

Structural Model

Three separate PLS analyses (one with full data and two with subsets of the data) were conducted to test the hypotheses developed for this study.

Hypothesis Testing with Full Data

As hypothesized, *distrust* exerts significant negative impact on *intention to use the PRA* ($\beta = -0.116, p < 0.05$), supporting **H2**. However, contrary to **H1**, the direct impact of *trust* on *intention* was negligible ($\beta = 0.066, p > 0.1$). *Trust* exerts significant positive impact on *perceived usefulness* ($\beta = 0.730, p < 0.01$), supporting **H3**. However, contrary to **H4**, the impact of *distrust* on *perceived usefulness* was negligible ($\beta = -0.069, p > 0.1$). The results also support the positive relationship between *perceived usefulness* and *intention* (**H7**, $\beta = 0.750, p < 0.01$) as well as that between *perceived ease of use* and *perceived usefulness* (**H8**, $\beta = 0.131, p < 0.05$).

Hypothesis Testing with Split Data

To test H5-H6, the full data set was split into two subsets, with membership in a particular subset dependent on whether a participant had noticed anomalies in the PRA’s recommendations. Upon completion of the experimental task at the e-commerce website, participants were asked three questions about whether they had noticed anything anomalous or unusual in the PRA’s recommendations. Responses of participants who answered “Neutral” (an indication of uncertainty) to any of the three questions were excluded from the split data analysis. Responses of those who answered “Mildly Agree”, “Agree”, or “Strongly Agree” to any of these questions were coded as “1”, meaning that they have noticed anomalies in the PRA’s recommendations. Responses of the others were coded as “0”, meaning that they have not noticed any anomaly in the PRA’s recommendations. In total, 121 participants (out of 256) noticed anomalies in the PRA’s recommendation whereas 106 participants did not.

Separate PLS analysis was conducted for each subset of the data. As illustrated in Figure 2, for participants who have not noticed anomalies in the PRA’s recommendations, *trust* exerts significant positive impact on *intention to use the PRA* ($\beta = 0.221, p < 0.05$). However, the impact of *distrust* on *intention* was negligible ($\beta = -0.018, p > 0.1$). A comparison of the two path coefficients was performed via the formula below:

$$t = \frac{PC1 - PC2}{\sqrt{se1^2 + se2^2}}$$

where PC_i = path coefficient in structural model under comparison, se_i = standard error of path coefficient PC_i and t = t -statistic with $n - 1$ degrees of freedom. Result of the computation reveals that the path coefficient between *trust* and *intention* is significantly larger than that between *distrust* and *intention* ($t(105) = 2.42, p < 0.05$), suggesting that *trust* is a more important predictor than *distrust* in this situation. **H6** is thus supported.

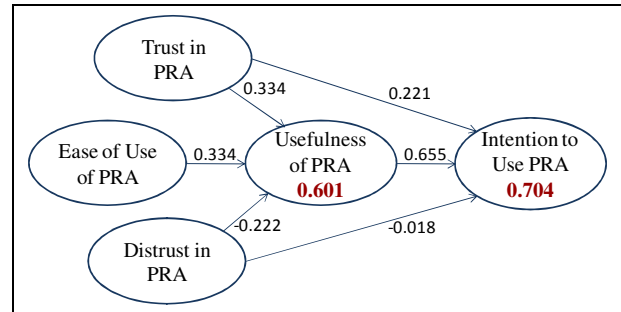


Figure 2. PLS Testing Results for Dataset Containing Those Who Have Not Noticed Any Anomaly

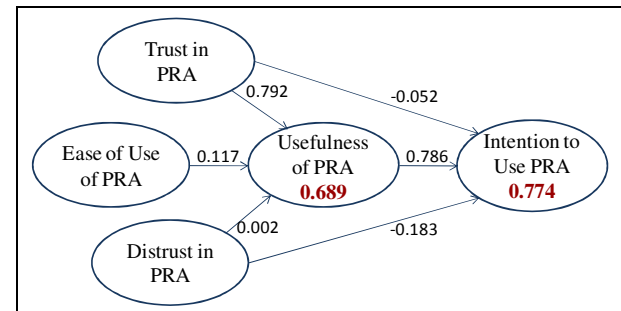


Figure 3. PLS Testing Results for Dataset Containing Those Who Have Noticed Anomalies

However, for participants who had noticed anomalies in the PRA’s recommendations (see Figure 3), *distrust* exerts significant negative impact on *intention to use the PRA* ($\beta = -0.183, p < 0.01$) whereas *trust* does not ($\beta = -0.052, p > 0.1$). A comparison of the two path coefficients reveals that the path coefficient between *distrust* and *intention* is larger than that between *trust* and *intention* ($t(120) = 1.79, p = 0.076$), suggesting that *distrust* is a more important predictor than *trust* in this situation. Thus, **H5** is supported (though not at $p < 0.05$ level).

Figure 2 and Figure 3 also reveal that, whereas both *trust* and *distrust* exert significant impact on *perceived usefulness of the PRA* ($\beta = 0.334, p < 0.01$; $\beta = -0.222, p < 0.05$) for participants who have not noticed anomalies in the PRA’s recommendations, only *trust* exerts significant positive impact on *perceived usefulness of the PRA* ($\beta = 0.792, p < 0.01$) for those who have noticed anomalies in the PRA’s recommendations.

CONCLUSION AND DISCUSSION

The results of the study provide evidence that *trust* and *distrust* are distinct and are both indispensable concepts in a deception detection context. Having both *trust* and *distrust* in the research model enables us to reach a fuller understanding of factors affecting consumers' usage *intentions*. More importantly, the results demonstrate that *trust* and *distrust* have asymmetric effects on consumers' *intention to use the PRA* -- their relative importance of in predicting *intention* is dependent on the level of risk embedded in a particular situation. Whereas *distrust* is more strongly related to consumer *intention* in a high-risk situation (i.e., when consumers have noticed anomalies in the PRA's recommendations), *trust* is the more important predictor of consumer *intention* in a low-risk situation (i.e., when consumers have not noticed anomalies in the PRA's recommendations). The results of the study have also revealed differential relationships between *trust/distrust* and *perceived usefulness* in different risk situations. *Perceived usefulness* is strongly affected by both *trust* and *distrust* in a low-risk situation, when participants have noticed anomalies in the PRA's recommendations. However, in high-risk situation, when participants have not noticed any anomaly in the PRA's recommendations, *perceived usefulness* is affected by *trust* alone (but not *distrust*). This suggests that, if consumers become distrustful of a PRA in a high-risk situation, they will have no intention to use the PRA, without even considering the utility of the PRA.

Prior research has demonstrated the discriminant validity of *trust* and *distrust* and shown (to a limited extent) that trust and distrust may have different antecedents and consequences (e.g., Cho, 2006; McKnight et al., 2004; McKnight and Choudhury, 2006). Prior research also suggests that *distrust* is likely to have greater effect on behavioral intentions than *trust* (Cho, 2006; Dimoka, 2009), given that negative beliefs tend to weigh more on a decision than positive beliefs (Kahneman and Tversky, 1979). However, the results of this study caution against generalizing such an argument broadly, since the relative dominance of *trust* and *distrust* may vary across different situations. To our knowledge, this study was the first to explore the differential effects of *trust* and *distrust* on the same outcome variable (i.e., *intention*) in situations of varying level of risk. This study not only sheds light on the dynamics of *trust* and *distrust* relations in a deception detection context but also contributes to a theory-building in trust and distrust in general.

For practitioners, the implications of this study are that the risk faced by the customer will dictate if online vendors should focus on managing trust or distrust. For example, if a customer does not perceive high-risk in using a PRA then trust should be enhanced for the user to accept the PRA's advice; in such cases, explanations provided by PRAs have been shown to be effective in increasing trust (Wang and Benbasat, 2008). However, if a user feels that a PRA use is risky, maybe due to being a

first time user or based on prior unsatisfactory experience, then institutional assurances (third party certifications or regulatory remedies such as compensation) may be better to reduce the effects of distrust.

ACKNOWLEDGMENTS

The authors acknowledge with gratitude the generous support of Hong Kong Baptist University for the project (FRG2/10-11/009) without which the timely production of the current publication would not have been feasible.

REFERENCES

1. Cho, J. (2006) The mechanism of trust and distrust formation and their relational outcomes, *Journal of Retailing*, **82**, 25-35.
2. Dimoka, A. (2009) What Does the Brain Tell Us about Trust and Distrust? Evidence from a Functional Neuroimaging Study, *Management Information Systems Quarterly*, **Forthcoming**.
3. Grazioli, S. and Jarvenpaa, S. L. (2000) Perils of Internet fraud: An empirical investigation of deception and trust with experienced Internet consumers, *IEEE Transaction on Systems, Man, and Cybernetics*, **30**, 395-410.
4. Johnson, P. E., Grazioli, S. and Jamal, K. (1993) Fraud detection: Intentionality and deception in cognition, *Accounting, Organizations and Society*, **18**, 467-488.
5. Komiak, S. X., Wang, W. and Benbasat, I. (2004/2005) Trust Building in Virtual Salespersons versus in Human Salespersons: Similarities and Differences, *e-Service Journal* **3**, 49-63.
6. Lewicki, R. J., Mcallister, D. J. and Bies, R. J. (1998) In *Academy of Management Review*, Vol. 23 Academy of Management, pp. 438.
7. McKnight, D. H. and Choudhury, V. (2006) Distrust and trust in B2C E-Commerce: Do they differ, *Proceedings of 8th International Conference on Electronic Commerce*, Fredericton, Canada.
8. Pavlou, P. A. (2003) Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model, *International Journal of Electronic Commerce*, **7**, 101-134.
9. Pavlou, P. A. and Gefen, D. (2005) Psychological contract violation in online marketplaces: Antecedents, consequences, and moderating role, *Information Systems Research*, **16**, 372-399.
10. Wang, W. and Benbasat, I. (2005) Trust In and Adoption of Online Recommendation Agents, *J AIS*, **6**.
11. Xiao, B. (2010) *Product-Related Deceptive Information Practices in B2C E-Commerce: Formation, Outcomes, and Detection*, Unpublished PhD Dissertation, University of British Columbia, Vancouver.
12. Xiao, B. and Benbasat, I. (2007) E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact, *MIS Quarterly*, **31**, 137-209.