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RESEARCH ARTICLE

THE EFFECTS OF PERSONALIZATION AND FAMILIARITY ON TRUST AND ADOPTION OF RECOMMENDATION AGENTS[1]

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Abstract

In the context of personalization technologies, such as Web-based product-brokering recommendation agents (RAs) in electronic commerce, existing technology acceptance theories need to be expanded to take into account not only the cognitive beliefs leading to adoption behavior, but also the affect elicited by the personalized nature of the technology. This study takes a trust-centered, cognitive and emotional balanced perspective to study RA adoption. Grounded on the theory of reasoned action, the IT adoption literature, and the trust literature, this study theoretically articulates and empirically examines the effects of perceived personalization and familiarity on cognitive trust and emotional trust in an RA, and the impact of cognitive trust and emotional trust on the intention to adopt the RA either as a decision aid or as a delegated agent.

*An experiment was conducted using two commercial RAs. PLS analysis results provide empirical support for the proposed theoretical perspective. Perceived personalization significantly increases customers' intention to adopt by increasing cognitive trust and emotional trust. Emotional trust plays an important role beyond cognitive trust in determining customers' intention to adopt. Emotional trust **fully** mediates the impact of cognitive trust on the intention to adopt the RA as a delegated agent, while it only **partially** mediates the impact of cognitive trust on the intention to adopt the RA as a decision aid. Familiarity increases the intention to adopt through cognitive trust and emotional trust.*

Keywords: Trust, electronic commerce, adoption, personalization, familiarity, cognitive trust, emotional trust, recommendation agent, delegation

Introduction

Web-based product-brokering recommendation agents (RAs) are personalized computer agents that provide an online consumer with recommendations on what product to buy based on that consumer's individual needs (Maes et al. 1999). RAs (e.g., www.ActiveBuyersGuide.com), unlike search engines (e.g., www.google.com), possess a certain amount of product knowledge to help customers configure their needs. RAs are examples of web-based personalization technologies (Murthi and Sarkar 2003) which enable firms to increase their

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revenues (Shaffer and Zhang 2000), reduce their costs of collecting consumers' preference information (Dewan et al. 2000), and facilitate product customization (Dewan et al. 2000). RAs also help customers to overcome information overload on the Internet and improve their decision making (Häubl and Trifts 2000). However, RAs have to be widely used by online customers before their benefits accrue to firms and customers. Hence, the focus of this research is to investigate why and how individual customers will adopt RAs.

Unlike a generic information technology, an RA is a *personalized*, advice-giving technology. Such a unique personal relationship requires a new lens for understanding users' adoption of RAs. The existing theories of IT adoption, as summarized in Venkatesh et al. (2003), have mainly a cognitive orientation. For example, the technology acceptance model (TAM) suggests that the intention to adopt an IT is influenced by the perceived usefulness and perceived ease-of-use of the IT (Davis 1989). The unified theory of acceptance and use of technology (UTAUT) posits that the intention to accept and use an IT is affected by performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al. 2003). In traditional IT adoption studies, most users are organizational employees using traditional IT (e.g., spreadsheets) for work-related purposes (Kim et al. 2004), contexts in which cognitive factors may dominate adoption decisions. In contrast, this study seeks to investigate whether or not perceived personalization and familiarity influence RA adoption by employing a trust-centered lens with a balanced cognitive and emotional perspective. Such a perspective is used for two reasons.

First, human experience contains both cognitive and emotional aspects. Thus, users' affective reactions (e.g., feeling comfortable or not) to IT need to be considered. Second, RA adoption may not be a purely cognitive decision because RA users play the dual roles of both IT users and customers. In many consumption situations at the individual consumer level, customers' affective reactions have an impact on their choices (Derbaix 1995). Particularly, customers in B2C (business-to-consumer) e-commerce choose products in a context in which they cannot directly experience the products (Jiang and Benbasat 2004; Suh and Lee 2005) and in which they are distant from the sellers. Such a context will make the customers' choices less cognitively dominated due to uncertainties about products and sellers. Indeed, some IS researchers have suggested that affect about IT does influence adoption intention (Hu et al. 2004; Kim et al. 2004). This study follows and extends this line of research by delineating cognitive trust and emotional trust, and investigating their respective roles in RA adoption. The key point of this study is that when an IT (e.g., an RA) becomes personalized, adoption by customers is not based solely on cognitive factors.

This research uses a trust-centered lens to study RA adoption. Trust is important in situations where there is a state of *dependence* between two parties and when this dependence entails *risk* (Chopra and Wallace 2003). Trust reduces the complexity of understanding by subjectively ruling out the risk of undesirable, yet possible, future behaviors from the trustee (Gefen et al. 2003; Luhmann 1979). In the context of RA adoption, given the amount of information overload and search complexity in e-commerce, customers *depend* on RAs for better decision making, usually *before* the veracity of recommendations can be assessed by actually experiencing the recommended products. *Risk* arises because customers are aware that the information provided by the RAs is of uncertain quality and that relying on poor information or poor reasoning on the part of the RA renders them vulnerable to faulty decisions (Chopra and Wallace 2003). Thus, RA adoption will largely rely on customer trust in the RAs. Recent IS literature emphasizes the significant impact of trust on IT adoption by customers in e-commerce (Gefen et al. 2003; McKnight et al. 2002). This study is derived from, and extends, the research on trust and IT adoption by investigating how RA personalization and familiarity affect RA adoption through enhancing cognitive trust and emotional trust in the RA. Perceived personalization indicates an RA's understanding of a particular customer's personal needs, while familiarity indicates the customer's understanding of the RA.

Our research model draws its theoretical foundation from the theory of reasoned action (TRA) (Fishbein and Ajzen 1975). In contrast to the traditional cognition–affect–intention framework used in much of the prior research, we use a trust-focused lens, where both cognition and affect are replaced by their counterparts related to trust, namely cognitive and emotional trust, respectively.

The next section of this paper elaborates on the theoretical foundations of the study and derives the hypotheses to be tested. The research method is then described, followed by a report of the results. The final section discusses the findings and provides concluding comments.

Theoretical Foundations and the Research Model

Theory of Reasoned Action (TRA)

Our research model draws its theoretical foundation from TRA (Fishbein and Ajzen 1975), which has been widely used by IS researchers to explain IT adoption (e.g., Davis et al. 1989; McKnight et al. 2002; Venkatesh et al. 2003).

According to TRA (Fishbein and Ajzen 1975, p. 16), an individual's behavior is predicted by his or her intention to perform this behavior. The intention is influenced by two factors: (1) attitude toward this behavior, which is a function of beliefs about consequences of this behavior, and (2) subjective norms concerning this behavior, which are a function of normative beliefs about this behavior. Attitude toward the behavior is a person's positive or negative feelings (*evaluative affect*) about performing the behavior; a subjective norm is a person's perception that most people who are important to him or her think he or she should or should not perform the behavior (Fishbein and Ajzen 1975).

In the context of IT adoption (a behavior), the effect of subjective norms on the intention to adopt is more salient when IT use is *mandatory* rather than voluntary (Miller and Hartwick 2002). The effect of subjective norms is greater in the absence of any experiential data. As users gain first-hand experience with an IT, first-hand, experience-based attitude gains prominence while subjective norms lose significance (Karahanna et al. 1999). Because the present study focuses on *voluntary* use of an RA by customers who have *first-hand experience* with the RA, our research model focuses on attitude, not subjective norms. This is consistent with prior IS research (e.g., Gefen et al. 2003) and the widely used TAM.

Cognitive Trust and Emotional Trust

Researchers have long acknowledged that trust is not easy to conceptualize (Gefen et al. 2003). Prior IS researchers (McKnight et al. 2002; McKnight et al. 1998) use TRA theory to categorize three common types of trust: (1) trusting belief (the trustor's perceptions that the trustee has attributes that are beneficial to the trustor), (2) trusting intention (the trustor's willingness to depend on a trustee in a given situation), and (3) disposition to trust (the extent to which a person displays a tendency to be willing to depend on others across a broad spectrum of situations and persons). Most IS researchers define trust as trusting beliefs (for reviews, see, Gefen et al. 2003; Komiak and Benbasat 2004; McKnight et al. 2002). Trusting beliefs are the trustor's *cognitive* beliefs resulting from the trustor's attributional processes. In other words, the trustee's actions are observed, and the causes are attributed to the trustee's internal trust-related characteristics (e.g., competence and integrity).

The concept of trusting beliefs (McKnight et al. 2002) is consistent with the concept of cognitive trust, defined as a trustor's *rational expectations* that a trustee will have the necessary attributes to be relied upon (Komiak and Benbasat 2004). The concept of cognitive trust is derived from the theoretical perspective of viewing trust as a trustor's rational choice, a perspective that is rooted in sociological (Coleman 1990), economic (Williamson 1993), and political (Hardin 2002) theories. Choice is motivated by a conscious calculation of advantages, a calculation that in turn is based on an explicit and internally consistent value system (Schelling 1960). When the trustor believes that good reasons to trust have been identified, cognitive trust is developed (Lewis and Weigert 1985).

The dominance of conceptualizing trust as trusting beliefs indicates a cognitive orientation in trust research in IS field. Indeed, McKnight et al. state explicitly, "The distinction between trusting beliefs and trusting intention follows the Fishbein and Ajzen (1975) typology separating constructs into beliefs, attitude, intentions, and behaviors. We exclude attitudes and behaviors here so we can focus the article on *cognitive* concerns" (1998, p. 474). Similarly, Gefen et al. (2003) conceptualize trust as trusting beliefs in trustee's integrity, benevolence, ability, and predictability. They state, "trust as a *feeling*...has been previously studied in the context of interpersonal relationships, such as friendship and love. It is arguably irrelevant to a business transaction" (p. 60).

However, without emotional trust, cognitive trust is inadequate to account for how people actually make decisions about whether to trust or not. This is because (1) the rational choice perspective overstates people's cognitive capacities, the degree to which people engage in conscious calculation as well as the extent to which they possess stable values and orderly preferences (March 1994), and (2) the rational choice perspective affords too small a role to emotional and social influences on trust decisions (Kramer 1999). Komiak and Benbasat (2004) conceptualize trust, including trust in IT, as a combination of cognitive trust and emotional trust, based on the assumption that trust decisions usually involve both *reasoning* and *feeling*.

Emotional trust is defined as the extent to which one *feels* secure and comfortable about *relying* on the trustee (Komiak and Benbasat 2004). The concept of emotional trust is largely rooted in sociology (Holmes 1991; Lewis and Weigert 1985), psychology (Rempel et al. 1985), and marketing (Swan et al. 1999). Emotional trust includes a person's evaluation of cognitive beliefs, his or her gut feeling and faith (Rempel et al. 1985), and his or her evaluation of emotional reactions to the trustee. Thus, emotional trust can be either rational or irrational. It enables individuals to go beyond the available evidence to feel assured and comfortable about relying on the trustee (Holmes 1991; Komiak and Benbasat 2004; Lewis and

Weigert 1985). Emotional trust is not the same as affect-based trust that refers to the "emotional elements and social skills of trustees. Care and concern for the welfare of partners form the basis for affect-based trust" (Kanawattanachai and Yoo 2002, p. 190). Thus, the emotion in emotional trust refers to the *trustor*'s feeling toward *the behavior of relying on the trustee*, while the affect in affect-based trust refers to the *trustee*'s affect toward *the trustor*.

This study investigates the roles of both cognitive trust and emotional trust (Komiak and Benbasat 2004) in RA adoption, and is based on three reasons. First, other trust literature also suggests that cognitive trust and emotional trust are different concepts, as noted in the following quote: "Trust can be based upon the rational appraisal of a partner's reliability and competence, and upon *feelings* of concern and attraction" (Greenspan et al. 2000, p. 253). Second, the concept that trust decisions involve emotions is strongly supported by experimental findings in neurology (Adolphs 2002). Third, it is beneficial to include emotional trust in trust research, because an understanding of emotional trust, and the way it complements cognitive trust, will provide a fuller understanding of trust and IT adoption. As far as we know, no prior research has empirically examined the effects of emotional trust on IT adoption.

Adapting from Komiak and Benbasat's trust model, we define trust in an RA as follows: (1) cognitive trust in competence: a customer's *rational expectation* that an RA has the capability to provide good product recommendations; (2) cognitive trust in integrity: a customer's *rational expectation* that an RA will provide objective advice; and (3) emotional trust: a customer's *feelings* of security and comfort about relying on an RA for the decision on what to buy.

We distinguish cognitive trust in competence from cognitive trust in integrity, because they are conceptually different in that a trustee may be highly competent without integrity (e.g., may provide biased advice that is beneficial to the e-vendor who owns the RA) or be of high integrity without adequate competence. They also differ operationally (McKnight et al. 2002). We did not include cognitive trust in benevolence, because in the context of RA adoption, the RA's competence and integrity are the key indicators of cognitive trusting beliefs. This is because customers are mainly concerned with whether the RA has the competence required to provide them with relevant and customized advice. Customers are equally worried that the RA might be designed to be biased (integrity) toward recommending only those products that are most profitable for the e-vendor who provides and owns the RA. Benevolence is the perception that the trustee intends to act in the trustor's interest (McKnight et al. 2002), especially when new conditions arise for which a commitment was not made (Ganesan et al. 2003). Trust in an RA's benevolence may be difficult to assess since the trustor has to form the beliefs that RAs can exhibit care and goodwill that go beyond the pre-determined tasks of giving competent and honest advice, tasks RAs are designed to do.

Research Model and Hypotheses Development

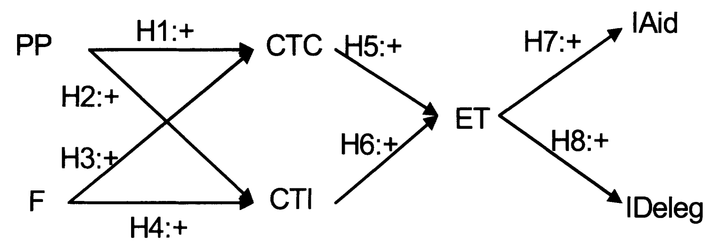
Using TRA as its theoretical framework (i.e., a belief–attitude–intention framework), our research model (Figure 1) describes the causal chain from perceived personalization and familiarity (perceptions) to cognitive trust (trusting beliefs) to emotional trust (trusting attitude) to specific use intentions (trusting intention). The target behavior in this study is RA adoption (i.e., customers' relying on the RA for their decision making), which is a trusting behavior. The research model includes the intention to adopt rather than the behavior of adoption, because the role of intention as a strong predictor of behavior has been well-established in IS (Davis 1989; Venkatesh et al. 2003) and reference disciplines (Davis et al. 2002).

We conceptualize cognitive trust as *beliefs* and emotional trust as an *attitude*. Belief is one's conviction of the reality of something, when based on examination of evidence. Cognitive trust in competence and cognitive trust in integrity are beliefs because they are a customer's conviction of the reality of the RA's competence and integrity, based on good rational reasons. Emotional trust is an attitude toward the behavior of RA adoption because it is an *evaluative affect* about *relying* on the RA. Attitude toward the *behavior* (emotional trust) is different from attitude toward the *trustee* (e.g., liking). For instance, a customer may feel secure about relying on an RA due to its competence and integrity, but he or she may not like it, due to the RA's interface or the style of interaction it imposes on the user.

In the rest of this section, the relationships in Figure 1, as well as the development of hypotheses, are explained in detail.

Personalization, Familiarity, and Cognitive Trust Beliefs

Perceived personalization is a customer's perception of an RA's personalization (i.e., the extent to which the RA understands and represents his or her personal needs). A product-brokering RA represents a customer's personal needs as a set



PP: perceived personalization. F: familiarity. CTC: cognitive trust in competence. CTI: cognitive trust in integrity. ET: emotional trust. IAid: intention to adopt as a decision aid. IDeleg: intention to adopt as a delegated agent.

Figure 1. The Research Model

of preferred product attributes and/or weights; it then filters the product information, calculates the ranking of the recommended products, and presents its recommendations, ranking, and explanations to the customer. In this case, perceived personalization means that the product attribute preferences used by the RA for its recommendation generation will effectively articulate the customer's personal needs and that the RA's product filtering strategy and ranking calculations are consistent with the customer's personal shopping strategy. For example, a customer may care about the battery life of her notebook computer, due to the large amount of time she spends in airports and on planes. If one RA allows her to specify a battery life attribute while another does not, then the first RA would have higher perceived personalization than would the second.

Perceived personalization will affect a customer's beliefs about an RA. An RA could achieve high personalization by asking better questions to articulate the customer's personal needs, including identifying all product attributes important to that particular customer, capturing the relative importance among different product attributes, and helping novice customers by mapping their shopping goals to product attribute specifications. A better representation of customer needs will be used by the RA's reasoning process to generate better recommendations. In addition, the reasoning process of a high personalization RA can better mimic the customer's personal decision-making process than that of a low personalization RA. Both better representation of customer needs and better reasoning process will generate more relevant and better-customized recommendations. Thus, the perception of high RA personalization is a good and rational reason for the customer to believe in the RA's competence.

> **H1**: Perceived personalization will increase cognitive trust in an RA's competence.

An RA's integrity refers to the extent to which the RA's advice is perceived to be unbiased. An RA might have been designed to provide biased information. For example, an RA, unbeknownst to customers, may generate product recommendations only from certain product brands that are available from its owner or from which its owner can receive commissions.

Compared to a lower personalization RA, a higher personalization RA will be more effective in articulating a customer's personal needs, and its reasoning will be more similar to the customer's decision-making process; thus, the higher personalization RA can better *understand* and *represent* the customer's personal preferences. A higher personalization RA can understand a customer's personal preferences better; therefore, it is able to generate a more relevant and better-customized choice set for that particular customer. Because the higher personalization RA can better represent the customer's personal preferences, it is more likely that the customer will believe that this RA will rank the relevance of choices in the choice set by only employing his or her personal preferences instead of using any other party's preferences. Both the more relevant choice set and the perception of the RA's using his or her own preferences for ranking will increase the customer's perception that the RA's advice is unbiased. Therefore, an RA's perceived personalization will increase the customer's trust in the RA's integrity.

> **H2**: Perceived personalization will increase cognitive trust in an RA's integrity.

Familiarity is one's understanding of an entity, often based on previous interactions, experience, and learning of "the what, who, how, and when of what is happening" (Gefen et al. 2003, p. 63). Familiarity with an RA is acquired through one's prior and direct experiential exchanges with the RA. What the customer learns can include how to express her or his personal needs in the RA, what types of questions the RA asks, what kinds of explanations of product attributes or reasoning the RA gives, and how to read and compare the details of the products recommended and ranked by the RA.

In general, familiarity may increase either trust or distrust, depending on whether the trustor's experience with the trustee is positive or negative (Luhmann 1979). In the context of RA adoption, assuming that the same RA has provided satisfactory recommendations in prior utilization (which means that customers' experience with the RA is positive), familiarity will increase trust in the RA. This assumption is likely to be valid in the context of RA usage, based on prior research that has consistently suggested that RAs provide valuable advice to help customers and improve their effectiveness and efficiency in purchasing decision making (Häubl and Trifts 2000; Lynch and Ariely 2000). In our empirical study, we tested this assumption, and the results confirmed that this assumption was valid.[2]

We expect that familiarity will increase cognitive trust in an RA's competence. After completing several shopping tasks with an RA, a customer will be more familiar with it, and will acquire a cognitive map of the procedures involved in that RA. Such a cognitive map provides the customer with an additional tool to use the same RA more quickly, with greater ease, and with fewer errors (Simon and Gilmartin 1973). Therefore, with higher familiarity (and if the recommendations provided by the RA in prior interactions were deemed satisfactory), it is likely the customer will think the same RA is more effective and efficient.

> **H3**: Familiarity will increase cognitive trust in an RA's competence.

Familiarity reduces the uncertainty of expectation through increased understanding of what has happened in the past (Luhmann 1979). Familiarity allows customers to accumulate trust-relevant knowledge about the trustee. Trust is created when the trustor's knowledge about the trustee allows the trustor to predict the trustee's behavior in the future (Doney and Cannon 1997). If a customer did not see any sign of biased or false information given by the RA during the prior interactions with the RA, then the customer may predict that the RA will remain honest and objective in the future. Thus, familiarity will increase cognitive trust in the RA's integrity.

> **H4**: Familiarity will increase cognitive trust in the RA's integrity.

Cognitive Trust, Emotional Trust, and Intention to Adopt

The relationships among cognitive trust, emotional trust, and intention to adopt fit well with the belief–attitude–intention framework suggested by TRA. According to TRA, a person's attitude toward performing a given behavior is the affective evaluation of the total effects of his or her beliefs that performing the behavior will lead to certain consequences and subsequent evaluation of those consequences. This attitude is a major determinant of the person's intention to perform the behavior in question (Fishbein and Ajzen 1975). In the context of RA adoption, a high level of cognitive trust in an RA's competence means that the customer believes that relying on the RA will generate well-customized recommendations. A high level of cognitive trust in an RA's integrity means that the customer believes that relying on the RA will provide truthful and objective recommendations. The customer holding such beliefs is likely to have stronger feelings of security and comfort about relying on the RA for his or her decision making. Thus,

> **H5**: Cognitive trust in competence will increase emotional trust.

> **H6**: Cognitive trust in integrity will increase emotional trust.

Instead of examining a customer's intention to adopt an RA as a unitary concept, the current study goes one step further by examining a customer's *intention of how to adopt an RA*. The intention to adopt is the extent to which one is willing to *depend* on an RA for decision making. When a customer decides to adopt an RA, she or he would also decide to what extent to depend on the RA. According to the seminal work on RAs by Maes et al. (1999), a customer can use a personalized and semi-automatic computer agent (e.g., an RA) to *assist* or to *automate* some of the stages of shopping decision making. We will label these as decision aid and delegated

[2]In the main experiment, after each use of the RA to shop, each participant rated his or her agreement level with a question: "I trust the recommended product" (1 = strongly disagree, 7 = strongly agree). In the low-familiarity group, after one use of the RA, the average trust in the recommended product was 5.7. In the high-familiarity groups, the average trust in the recommended products after the first, second, and third use of the RA were 5.2, 5.4, and 5.4, respectively. All the means were significantly higher than the neutral level 4.0, which means that the RA did provide satisfactory recommendations.

agent, respectively. *The intention to adopt as a decision aid* is the extent to which a customer is willing to let an RA narrow down the choices that she or he will then evaluate to make a purchase decision. *The intention to adopt as a delegated agent* is the extent to which a customer is willing to let the RA make a decision on her or his behalf about what to buy.

The two intentions are related but different enough to merit separate consideration. They are both intentions to adopt an RA to support one's purchasing decision making. However, they are different in terms of the level of customer dependence on the RA for decision making. When customers intend to use an RA as a *delegated agent*, they will accept the RA's product recommendations *without* carefully examining the RA's recommendations or explanations. In contrast, when customers intend to use an RA as a *decision aid*, they will *carefully examine* the RA's recommendations and explanations before they make the final decision themselves. When customers intend to adopt an RA as a delegated agent rather than as a decision aid, the customers' dependence on the RA is higher, and their decision making is more efficient due to the saved time and effort. When customers intend to adopt an RA as a decision aid rather than as a delegated agent, their dependence on the RA is lower, and their decision making will be more effective but less efficient because their decisions will be exactly what they want, at the expense of more time and effort spent examining the RA's recommendations and explanations. We investigate both intentions because we are interested in both how to increase customers' intention to adopt an RA (i.e., customer dependence on an RA), and the identification of factors that will increase the level of customer dependence on the RA.

According to TRA, attitude toward a behavior will predict the intention to perform the behavior. Customers are more likely to intend to adopt an RA when they have a high level of emotional trust in (i.e., a positive attitude toward) the RA. Thus,

> **H7**: Emotional trust will increase the intention to use an RA as a decision aid.

> **H8**: Emotional trust will increase the intention to use an RA as a delegated agent.

While the research model (Figure 1) predicts that perceived personalization and familiarity (perceptions) would affect emotional trust (attitude) through cognitive trust (beliefs), we would like to recognize the possibility of unmediated effects. For example, perceived personalization may directly affect emotional trust, because with a higher personalization RA, customers will see more similarities between their own needs and what the RA is doing, and more perceived similarities would invoke a sense of higher comfort and security about relying on the RA. In line with TRA, our research model only hypothesizes indirect effects from perceptions to attitude (perceptions → beliefs → attitude). However, we do not rule out the possibility of such direct effects (perceptions → attitude). Therefore, we performed tests for full and partial mediation effects, as discussed later in the "Structural Model" section.

Research Method

The hypotheses were tested in an experiment in which each participant used a commercial RA online to shop for products that they were interested in buying. A 2 × 2 factorial design was used. The treatments were personalization (low versus high) and familiarity (low versus high) (Table 1). Both were between-subject factors.

Independent Variable: Perceived Personalization

Based on our survey of commercial RAs online, and on a pilot test with 23 participants, two RAs were chosen from the same company: www.activebuyerguide.com. The RA shown in Figure 2 represents the RA with higher personalization than that shown in Figure 3.

These two RAs were identical in many aspects. Both were constraint-satisfaction RAs, in that customers specified all of the product features they desired, and the RA then gave each customer a list of products, ordered by how well the products satisfied the customer's constraints (Ansari et al. 2000; Maes et al. 1999). The two RAs used the same strategy to filter products available over the Internet. If a customer used both RAs to shop for the same product, both RAs provided exactly the same product attributes and the same levels of each product attribute for comparative specifications. Both RAs offered the same explanations for each product attribute.

We expected the two RAs to differ in their *perceived* personalization levels. Customers using the high-personalization RA could click the "get advice" hyperlink to answer *need-based* questions; based on these answers, the RA would suggest the appropriate specifications of product attributes. In contrast, the low-personalization RA asked customers to specify the preferred level of each product attribute, without the help of need-based questions. The high-personalization RA also gave customers an opportunity to specify the relative

Table 1. Experimental Design

		Familiarity	
		Low	**High**
Perceived personalization	**Low**	Group1 (23)	Group2 (25)
	High	Group3 (28)	Group4 (24)

Note: 100 subjects were randomly assigned into the four groups.

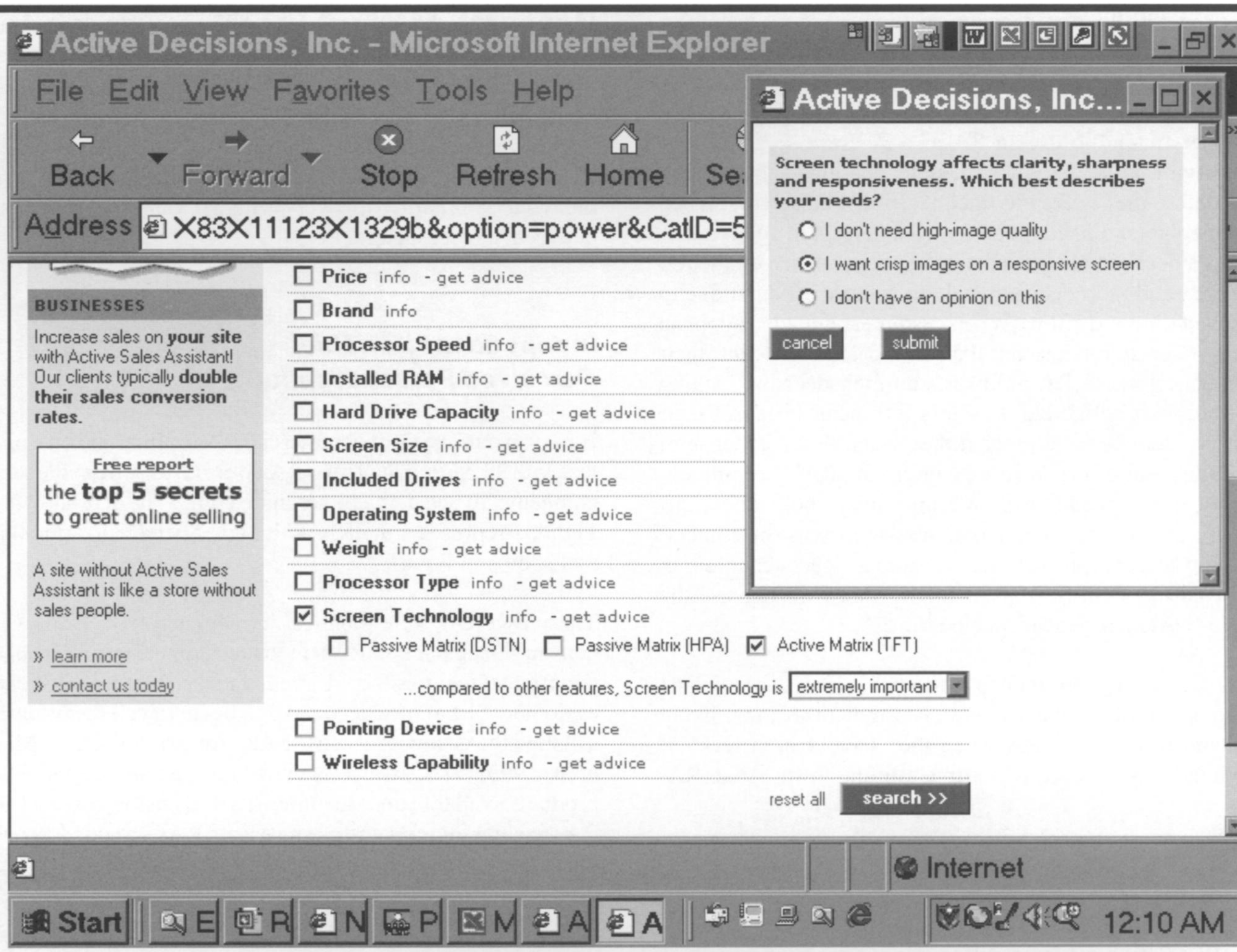


Figure 2. Screen Shot of the High-Personalization RA

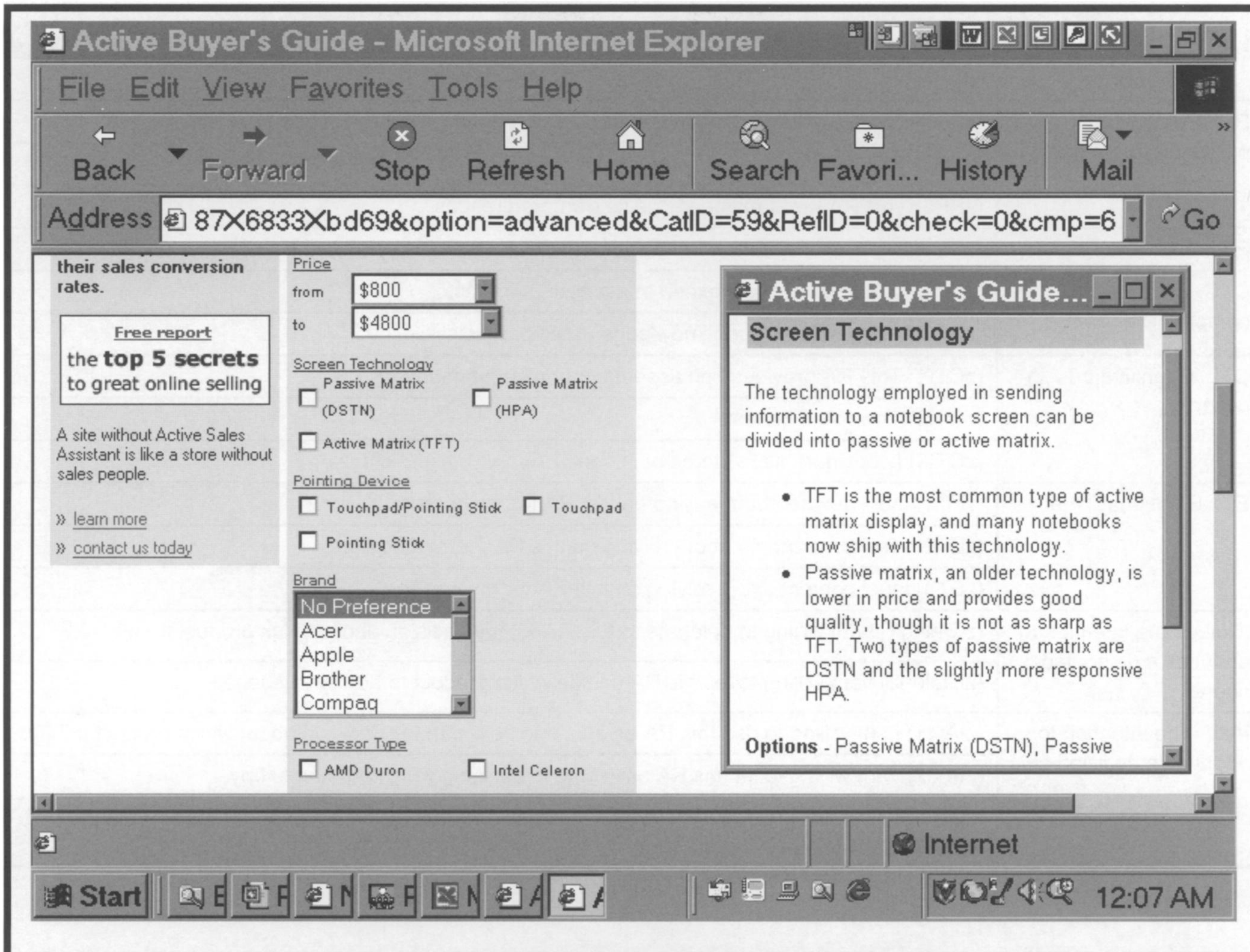


Figure 3. Screen Shot of the Low-Personalization RA

importance of each attribute, whereas the low-personalization RA did not. The availability of need-based questions (Grenci and Todd 2002) and weight questions was expected to increase customers' perception that the high-personalization RA can more effectively understand and represent their personal needs than the low-personalization RA.

A manipulation check for *perceived* personalization was conducted. At the end of each experimental session, after a participant had used one RA for shopping and answered all questions about trust and the intention to adopt, the participant was provided with the second RA. The participant tried out the second RA for as long as he or she wanted, then rated the perceived personalization of *both* RAs by answering three 7-point Likert questions (see Table 2). The manipulation was successful. On average, the 100 participants perceived that the two RAs had different personalization levels: high-personalization RA ($M = 5.8$, $SD = 1.0$) versus low-personalization RA ($M = 4.4$, $SD = 1.4$), $t(99) = 8.32$, $p < 0.001$. In addition, the between-treatment mean comparison also shows that the RAs were significantly different in terms of perceived personalization: high personalization RA (rated by participants in high-personalization groups only, $N = 52$, $M = 5.5$, $SD = 1.0$) versus low personalization RA (rated by participants in low-personalization groups only, $N = 48$, $M = 4.4$, $SD = 1.1$), one-way ANOVA, $F = 26.0$, $p < 0.001$.

Independent Variable: Familiarity

Two levels of familiarity were studied: low versus high. The participants in low-familiarity groups used the RA to shop for

Table 2. Constructs and Measures

Construct	Measure
PP: Perceived personalization	(zPP1) This RA understands my needs.
	(zPP2) This RA knows what I want.
	(zPP3) This RA takes my needs as its own preferences.
F: Familiarity	(zF1) I am familiar with how this RA makes its recommendation.
CTC: Cognitive trust in competence	(zCTC1) This RA is a real expert in assessing products.
	(zCTC2) This RA has good knowledge about products.
CTI: Cognitive trust in integrity	(zCTI1) This RA provides unbiased product recommendations.
	(zCTI2) This RA is honest.
	(zCTI3) I consider this RA to be of integrity.
ET: Emotional Trust	(zET1) I feel secure about relying on this RA for my decision.
	(zET2) I feel comfortable about relying on this RA for my decision.
	(zET3) I feel content about relying on this RA for my decision.
IDeleg: the intention to adopt as a delegated agent	(zIDeleg1) I am willing to delegate to this RA for my decision about which product to buy.
	(zIDeleg2) I am willing to let this RA decide which product to buy on my behalf.
IAid: The intention to adopt as a decision aid	(zIAid1) I am willing to use this RA as an aid to help with my decision about which product to buy.
	(zIAid2) I am willing to let this RA assist me in deciding which product to buy.
	(zIAid3) I am willing to use this RA as a tool that suggests to me a number of products from which I can choose.

one product: a notebook computer. The participants in high-familiarity groups used the same RA to shop for three products: a notebook computer, a desktop PC, and a digital camera. These three products were similar in nature (all were consumer electronic products) with similar levels of complexity (the RA considered about 11 attributes for each product). We chose these products because our participants (university students) indicated high interest in buying them. We chose three interactions to manipulate familiarity, because our pilot test with 23 participants showed that more than three interactions led to subject fatigue, while three were enough for the participants' trust to reach a steady state level.[3]

A manipulation check for familiarity was performed. After shopping for each product, each participant rated his or her agreement level with a statement: "I am familiar with how this RA makes its recommendation" (1 = strongly disagree, 7 = strongly agree). The familiarity scores provided by the low-familiarity group participants (after using the RA to shop for the one and only product) were compared to the scores provided by the high-familiarity group participants after shopping for their third product. The manipulation of familiarity was successful: high familiarity groups ($M = 5.5$, $SD = 1.1$) versus low familiarity groups $M = 4.6$, $SD = 1.8$), one-way ANOVA, $F = 5.4$, $p < 0.01$.

Dependent Variables: Measurement Development

We developed new measures (Table 2) by adopting (1) a three-step method of instrument development (Moore and Benbasat 1991): scale creation, scale development (three

[3] In the pilot test, each participant in the high-familiarity group answered a question about trust level after the first, second, and third use of the RA to shop for the three products, respectively. The trust level reported after using the RA for the first time was significantly different than that reported after using it for the second time, while the trust levels after the second and the third use, respectively, were *not* significantly different, indicating that the trust level reached a stable level after three interactions.

rounds of card sorting performed by a total of 18 participants), and scale testing via factor analysis in a pilot test with 162 participants; and (2) a PLS measurement model in the main experiment (100 participants) (Barclay et al. 1995). The descriptive statistics of dependent variables are shown in Table 3. The results of validity and reliability tests are discussed in the "Data Analysis and Results" section.

Participants and Experimental Procedures

Participants' characteristics are shown in Table 4. Data was collected in 2002 from 100 student participants enrolled in a North American business school. All volunteers were prescreened; only those who had shopped online before and those who were interested in buying the three products (i.e., notebook computer, desktop, and digital camera) were invited to participate. Therefore, the participants were interested potential customers when they took part in the experiment. The incentive for participation was a monetary reward ($15) plus one mark in a course evaluation. To further motivate the participants to view the experiment as a serious online shopping session, they were told before the experiment that one participant, selected by a random draw, would receive $400 to actually purchase the product that he or she decided to buy during the experiment. Participants were randomly assigned to one of four treatment groups (Table 1). Background checks indicated that there were no significant differences among the groups in terms of their previous experience with online shopping or online RA use.

Each participant took the experiment individually and was allowed to take as much time as needed. Most participants spent between 75 and 100 minutes. The procedures were

(1) Each participant read an information sheet stating that he or she would be testing a new RA. He or she then completed a consent form, a background questionnaire, and a tutorial about RAs.

(2) Each participant used an RA to shop for one product (i.e., notebook computer).

(3) Each participant answered the manipulation check question about familiarity. Whereas participants in low-familiarity groups proceeded to step 4, those in high-familiarity groups used the same RA to shop for desktop and digital camera by repeating steps 2 and 3 before proceeding to step 4.

(4) Each participant completed a questionnaire about trust and the intention to adopt. This questionnaire was completed only once by each participant.

(5) Each participant was provided with the second RA, tried it out for as long as wished, and then rated the perceived personalization level for each of the two RAs.

Data Analysis and Results

PLS (partial least squares, PLS-Graph version 3.00) was used for data analysis. Structural equation modeling (SEM) analysis was chosen over regression analysis, because SEM can analyze all of the paths in one analysis (Barclay et al. 1995; Gefen et al. 2000). Within SEM, PLS was chosen over LISREL because this study aims at theory development instead of theory testing. Whereas LISREL requires a sound theory base, PLS supports exploratory research (Barclay et al. 1995; Gefen et al. 2000).

PLS provides the analysis of both a structural model (assessing relationships among theoretical constructs) and a measurement model (assessing the reliability and validity of measures). In the model tested, all constructs were modeled as reflective, because their measurement items are manifestations of these constructs (Barclay et al. 1995) and because these items covary (Chin 1998). The manipulation check scores for independent variables were used in the model, because they reflected the participants' perceptions of personalization and familiarity affected by the treatments. All measurement items were standardized.

Measurement Model

Convergent validity is assessed by (1) reliability of items, (2) composite reliability of constructs, (3) average variance extracted (AVE) (Barclay et al. 1995; Hu et al. 2004), and (4) factor analysis results. Examining each item's loading on its corresponding construct assesses reliability of items. Barclay et al. (1995) suggest that, as a rule of thumb, the item loading should exceed 0.70. In this study, the loading of each item meets this criterion (Table 5). Regarding internal consistency (reliability), composite reliability scores for every construct (ranging from 0.89 to 0.95, as shown in Table 6) are well above 0.70, which is the suggested benchmark for acceptable reliability (Barclay et al. 1995; Fornell and Larcker 1981). AVE measures the amount of variance that a construct captures from its indicators relative to the amount due to measurement error (Chin 1998). It is recommended to exceed 0.50 (Hu et al. 2004). Table 6 shows that AVE score for every construct, ranging from 0.79 to 0.89, satisfies this requirement. In addition, to show good convergent validity in factor analysis results, all of the items should load highly on

Table 3. Descriptive Statistics of Dependent Variables

Constructs	Mean	Standard Deviation
CTC	5.60	1.09
CTI	5.36	1.18
ET	4.81	1.38
IDeleg	4.01	1.47
IAid	5.70	1.37

Note: All measures are 7-point scales with anchors 1 = strongly disagree and 7 = strongly agree.

Table 4. Participants' Characteristics

	Mean	Standard Deviation
Age	23.6 years	3.9 years
Comfortable with using computers*	6.4	1
Comfortable with shopping online*	4.8	1.6
Money spent online in 2001	$300	$424
Gender	Male	52
	Female	48
Graduate or Undergraduate	Undergraduate	70
	Graduate	30
Have used any online RA?	Yes	22
	No	78
Have used ActiveBuyersGuide.com for shopping?	Yes	0
	No	100

Note 1: Sample size = 100. No missing data.
Note 2: "Comfortable with using computers" and "Comfortable with shopping online" are 7-point scales with anchors 1 = strongly disagree and 7 = strongly agree.

Table 5. Outer Model Loadings

CTC		PP	
zCTC1	0.91**	zPP1	0.93**
zCTC2	0.87**	zPP2	0.93**
CTI		zPP3	0.92**
zCTI1	0.85**	**IDeleg**	
zCTI2	0.90**	zIDeleg1	0.95**
zCTI3	0.91**	zIDeleg2	0.93**
ET		**IAid**	
zET1	0.92**	zIAid1	0.94**
zET2	0.95**	zIAid2	0.85**
zET3	0.93**	zIAid3	0.92**

Note: **Significant at the 0.01 level.

their own latent variables. Hair et al. (1998, p. 11) suggest that loadings over 0.3 meet the minimal level, over 0.4 are considered more important, and 0.5 and greater practically significant. Tabachnick and Fidell (2000, p. 625) suggest that the loading of an item on its corresponding construct should be at least 0.32, and that loadings over 0.71 are excellent, and over 0.63 very good, over 0.55 good, over 0.45 fair. The factor analysis results in this study (Table 7) are satisfactory according to these criteria.

Discriminant validity is assessed by examining (1) factor analysis results, (2) cross-loadings, and (3) the relationship between correlations among constructs and the square root of AVEs (Chin 1998; Fornell and Larcker 1981). Factor analysis results (Table 7) show good discriminant validity, because all of the measurement items load highly on their own constructs but not highly on other constructs. An examination of cross-factor loadings (Table 8) also indicates good discriminant validity, because the loading of each measurement item on its assigned latent variables is larger than its loadings on any other constructs (Chin 1998; Gefen et al. 2000; Straub et al. 2004). Another criterion is that the square root of the AVEs should be greater than the correlations among the constructs, which indicates that more variance is shared between the construct and its indicators than with other constructs (Fornell and Larcker 1981). Table 6 shows that the square roots of all the AVEs (i.e., the numbers on the diagonal) are greater than the correlations among constructs (i.e., the off-diagonal numbers), indicating satisfactory discriminant validity of all the constructs.

Structural Model

In PLS analysis, examining the R^2 scores (i.e., variance accounted for) of endogenous variables and the structural paths assesses the explanatory power of a structural model. In this study, the model accounts for 25 to 58 percent of the variances (R^2 scores). In addition, all of the paths are significant at the level of 0.05 (Figure 4). Thus, the fit of the overall model is good.

The PLS analysis results (Figure 4) show that all the hypotheses are supported, thus the proposed theoretical model in Figure 1 is empirically supported. Perceived personalization increases cognitive trust in the RA's competence ($\beta = 0.44$, $p < 0.01$) and integrity ($\beta = 0.43$, $p < 0.01$). Familiarity increases cognitive trust in the RA's competence ($\beta = 0.12$, $p < 0.05$) and integrity ($\beta = 0.21$, $p < 0.05$). Cognitive trust in competence ($\beta = 0.52$, $p<0.01$) and cognitive trust in integrity ($\beta = 0.37$, $p < 0.01$) increase emotional trust. Emotional trust increases the customer's intention to adopt as a decision aid ($\beta = 0.72$, $p < 0.01$) and as a delegated agent ($\beta = 0.72$, $p < 0.01$).

A supplementary analysis of the existence of mediating effects (Table 9) reveals that cognitive trust in competence and cognitive trust in integrity only *partially* mediate the impact of perceived personalization on emotional trust. Cognitive trust in integrity *fully* mediates the effect of familiarity on emotional trust. Emotional trust only *partially* mediates the impact of cognitive trust in integrity on the intention to adopt the RA as a decision aid, while it *fully* mediates the impact of both cognitive trust beliefs on the intention to adopt the RA as a delegated agent. Figure 5 alters the hypothesized model (Figure 4) by allowing significant and direct effects between constructs that are not adjacent to each other in the causal chain. These direct effects (perceived personalization → emotional trust; cognitive trust in integrity → intention to adopt as a decision aid) show the partial mediating effects indicated above.

Discussion and Conclusions

Key Insights and Implications

Drawing on the TRA, trust, and IT adoption literature, this study theoretically articulates and empirically tests a model positing that the mutual understanding between an RA and a customer (i.e., an RA's perceived personalization and a customer's familiarity with the RA) increases the customer's intention to adopt the RA by increasing cognitive and emotional trust.

The Roles of Cognitive Trust and Emotional Trust in IT Adoption

Prior trust literature in IS mainly conceptualizes trust as trusting beliefs (e.g., Gefen et al. 2003; McKnight et al. 2002). This study uses a more comprehensive view to examine both cognitive and emotional components of customer trust in an RA, and extends prior trust models by (1) conceptualizing cognitive trust as *beliefs* and emotional trust as an *attitude*, and (2) measuring and empirically examining the relationship between cognitive and emotional trust.

The results show that cognitive trust in competence and cognitive trust in integrity are significantly and positively associated with emotional trust. The results are consistent with TRA, which posits that beliefs positively affect attitude (Fishbein and Ajzen 1975), and prior empirical studies in

Table 6. AVE and Correlations among Latent Constructs

Construct	Reliability	AVE	PP	F	CTC	CTI	ET	IDeleg	IAid
PP	0.95	0.86	**0.93**						
F	1.00	1.00	0.40	**1.00**					
CTC	0.89	0.79	0.48	0.30	**0.89**				
CTI	0.92	0.79	0.52	0.38	0.45	**0.89**			
ET	0.95	0.87	0.62	0.32	0.69	0.60	**0.93**		
IDeleg	0.94	0.89	0.49	0.15	0.48	0.46	0.72	**0.94**	
IAid	0.93	0.82	0.54	0.31	0.57	0.55	0.72	0.52	**0.90**

Note: Diagonal elements are the square roots of average variance extracted (AVE).

Table 7. Factor Analysis Results

	PP	CTC	CTI	ET	IDeleg	IAid
zPP1	0.88					
zPP2	0.96					
zPP3	0.92					
zCTC1		0.76				
zCTC2		0.88				
zCTI1			0.92			
zCTI2			0.87			
zCTI3			0.69			
zET1				0.50		
zET2				0.50		
zET3				0.44	0.35	
zIDeleg1					0.79	
zIDeleg2					0.99	
zIAid1						0.80
zIAid2						0.82
zIAid3						0.81

Note 1: SPSS was used for factor analysis. Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.

Note 2: For the sake of clarity, this table does contain numbers that are lower than 0.30.

Table 8. Correlations between Measures and Latent Variables

	PP	F	CTC	CTI	ET	IDeleg	IAid
zPP1	0.93	0.37	0.46	0.54	0.60	0.44	0.54
zPP2	0.93	0.37	0.42	0.42	0.55	0.45	0.50
zPP3	0.92	0.37	0.46	0.47	0.58	0.46	0.44
zF1	0.40	1.00	0.30	0.38	0.32	0.15	0.31
zCTC1	0.46	0.29	0.91	0.34	0.65	0.47	0.48
zCTC2	0.40	0.24	0.87	0.47	0.56	0.38	0.54
zCTI1	0.36	0.26	0.34	0.85	0.43	0.34	0.36
zCTI2	0.44	0.30	0.37	0.90	0.49	0.41	0.48
zCTI3	0.54	0.42	0.46	0.91	0.65	0.47	0.58
zET1	0.59	0.32	0.65	0.56	0.92	0.66	0.67
zET2	0.62	0.33	0.63	0.59	0.95	0.66	0.68
zET3	0.55	0.26	0.64	0.53	0.93	0.68	0.66
zIDeleg1	0.49	0.21	0.51	0.50	0.74	0.96	0.53
zIDeleg2	0.42	0.07	0.39	0.36	0.61	0.93	0.44
zIAid1	0.51	0.40	0.60	0.47	0.71	0.49	0.94
aIAid2	0.47	0.14	0.44	0.42	0.58	0.47	0.85
zIAid3	0.48	0.28	0.50	0.59	0.66	0.45	0.92

Table 9. Results of Mediating Effect Tests

			Coefficient in Regressions				
IV	M	DV	IV → DV	IV → M	IV + M → DV		Mediating
					IV	M	
PP	CTC	ET	0.63**	0.48**	0.38**	0.50**	Partial
PP	CTI	ET	0.63**	0.52**	0.43**	0.38**	Partial
F	CTC	ET	0.33**	0.30**	0.13*	0.65**	Partial
F	CTI	ET	0.33**	0.38**	0.11	0.56**	Full
CTC	ET	IAid	0.58**	0.69**	0.17	0.61**	Full
CTI	ET	IAid	0.56**	0.69**	0.19*	0.61**	Partial
CTC	ET	IDeleg	0.48**	0.69**	-0.02	0.73**	Full
CTI	ET	IDeleg	0.47**	0.60**	0.05	0.69**	Full

Note 1: ** Significant at the 0.01 level; * Significant at the 0.05 level.

Note 2: IV: independent variable; M: mediator; DV: dependent variable.

Note 3: Mediating effects are tested by using the three-step method suggested by Baron and Kenny (1986) (Also see http://davidakenny.net/cm/mediate.htm. Last accessed on July 20, 2006.).

Step 1: IV → DV is significant.

Step 2: IV → M is significant.

Step 3: IV + M → DV: (a) If M is significant and IV is not significant, then M fully mediates the impact of IV on DV. (b) If both M and IV are significant, then M partially mediates the impact of IV on DV.

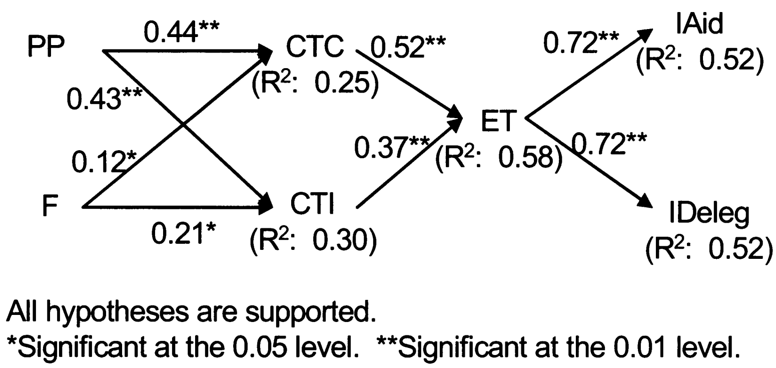


Figure 4. Results of PLS Analysis (Excluding Mediating Effects)

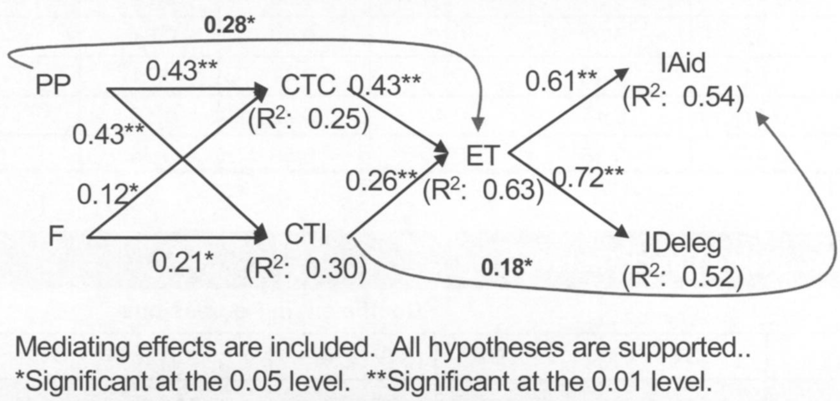


Figure 5. Results of PLS Analysis (Including Mediating Effects)

psychology, which suggest that emotion is almost always evoked by cognition (Curtin et al. 2001). They also partially agree with McKnight et al.'s (2002) findings that trusting beliefs positively affect trusting intentions. Part of their measure of trusting intentions (e.g., "I feel comfortable depending on the information provided by LegalAdvice.com") is similar to our measure of emotional trust ("I feel comfortable/secure/content about relying on the RA for decision making"). The difference is that this study separates McKnight et al.'s trusting intentions into trusting attitude (emotional trust) and trusting intentions (the intention to adopt).

While prior research in IS has examined the relationship between trust and IT adoption (Bahmanziari et al. 2003; Gefen et al. 2003; Pavlou 2003), this study is the first to examine the role of emotional trust in IT acceptance. The findings indicate that (1) emotional trust significantly increases the intention to adopt, and (2) emotional trust mediates *fully* the impact of cognitive trust beliefs on the intention to adopt as a delegated agent, while it only mediates *partially* the impact of cognitive trust in integrity on the intention to adopt as a decision aid. The latter result suggests that emotional trust plays a greater role when a customer's dependence on the RA is higher than when it is lower. The results on emotional trust and RA adoption may be explained by the rationale that (1) the customer's knowledge about how an RA functions, and on whose behalf, is necessarily incomplete; and (2) emotional trust enables customers to suspend their worries about the unknown regarding a new IT so that they can move forward to use it.

The findings in this study have both theoretical and practical implications. In terms of contributions to theory, these findings, if supported by additional research, would indicate that adding emotional trust and cognitive trust to IT adoption models in e-commerce contexts is appropriate. This is because customer trust is particularly important in such contexts, especially when the user feels that there may be an interpersonal relationship with the IT to be adopted, as is the case with an RA that represents the personal needs and goals of a particular customer. In terms of contributions to practice, the results indicate the importance of RA design to appeal to customers' emotional trust in addition to cognitive trust. RA designers may be able to increase emotional trust by better RA design, such as asking questions to identify the customer's awareness of the unknown and then providing tailored and timely answers, adding animation to the RA by using avatars for interfaces (Qiu and Benbasat 2005), embedding virtual reality technology within the RA for better product understanding (Jiang and Benbasat 2004), and assigning the RA a personality similar to the customer's own personality (Al-Natour et al. 2005). Improved functionality of the RA and evidence of integrity may also increase customers' emotional trust through increased cognitive trust.

In addition, cognitive trust in competence and cognitive trust in integrity have different impacts on the two intentions to adopt the RA. While both cognitive trust beliefs affect the intentions to adopt through emotional trust, the integrity belief is more important than the competence belief in determining the intention to adopt as a decision aid, while the competence belief is more influential in the intention to adopt as a delegated agent. This is because the total effect of the *integrity* belief (0.34) is higher than that of *competence* (0.26) on the intention to adopt as a *decision aid*. The integrity belief has a direct impact on the intention to adopt as a decision aid besides the indirect effect through emotional trust (Figure 5 and Table 9). Nevertheless, the total effect of the *competence* belief (0.31) is higher than that of *integrity* (0.19) on the intention to adopt the RA as a *delegated agent*. The results imply that, in order to increase a customer's dependence on the RA, RA design should be more focused on presenting evidence on competence, possibly through "how" explanations that reveal the RA's reasoning logic.

Perceived Personalization

Perceived personalization is a new construct not studied before in the IS literature. It directly increases cognitive trust in competence and integrity, as well as emotional trust. The total effect of perceived personalization on emotional trust, including direct effect (perceived personalization → emotional trust in Figure 5) and indirect effects (perceived personalization → cognitive trust beliefs → emotional trust), is 0.58. In other words, if perceived personalization increases by one standard deviation, then emotional trust will increase by 0.58 standard deviations. The total effect of perceived personalization on the intention to adopt as a decision aid is 0.43, while its total effect on the intention to adopt as a delegated agent is 0.42. These results show the value of increasing personalization levels in RA design.

The two cognitive trust beliefs only partially mediate the impact of perceived personalization on emotional trust, and a direct path exists from perceived personalization to emotional trust (Figure 5 and Table 9). These partial mediating results seem to indicate the existence of emotional processes that produce emotional trust directly, which are in addition to the cognitive processes that produce cognitive trust (shown in H1 and H2) which then contributes to emotional trust. One possible emotional process could be the development of the customer's identification with the RA. That is, when the customer perceives the RA to have higher personalization, the customer will develop a stronger sense of "we-ness" with the RA. Kramer et al. (2001) propose that individuals' *identification* with their group increases both their propensity to confer trust on other group members and their willingness to engage in trusting behavior themselves. Thus, increased identification with the RA may enhance a customer's perceptions of similarity with the RA, reduce perceived relational distance between himself or herself and the RA, and enhance the perceived consensus between his or her own decision making and that of the RA (Kramer et al. 2001). Consequently, the customer may perceive a smaller distinction between his or her own decisions and the RA's recommendation. Therefore, perceived personalization may increase emotional trust.

In summary, this study contributes to the IS literature by proposing theoretically and testing empirically a perspective that links perceived personalization of RA technology to the intention to adopt. It also provides empirical evidence on the impact of personalization on cognitive and emotional trust.

Limitations

First, the intention to use an RA either as a delegated agent or as a decision aid might be driven by the salience and importance of the product purchase decision to the consumer. For example, if a purchase is not consequential, a customer might be willing to delegate; but if it is consequential, the customer might choose to retain final decision-making power. This study does not address this issue since the experiment uses products in which the participants were interested and that were consequential to them. However, future research needs to measure the impact of product salience on the intention to use an RA as a delegated agent versus as a decision aid.

Second, the effect of brands in e-commerce has been found to be significantly high (see Brynjolfsson and Smith 2000). It is possible that if a consumer trusts or prefers a brand and the RA recommends it, then the consumer will feel that the RA has internalized his or her needs; thus, the measures of perceived personalization will probably reflect the extent to which the consumer projects his or her trust toward a particular brand onto the RA. Measures of perceived personalization might be biased because of this possibility.

Third, the ownership of an RA may affect a customer's trust in the RA. An RA may be owned by a company, by a third party, or by the customer. It is likely that a customer's trust in her or his own RA will be higher than her or his trust in one owned by a company or by a third party. In the information sheet for our experiment, the participants were told that they were going to use and evaluate an RA developed by a software company that wanted to sell it to customers for use as a virtual personal shopping assistant. While the RA's ownership does not affect the testing of the causal model in this paper, RA ownership should be considered before generalizing the results to other contexts.

Fourth, the use of student participants might threaten the external validity of this study, because there is no consensus on the extent to which university students are good surrogates for online customers. This study used university students for two reasons. First, these student participants were online customers. Second, prior empirical research in marketing suggests that where online behavior is concerned, a random sample of the general population of online consumers may not always be better than a student sample; results from a student sample can foreshadow the direction in which the general population is moving (Gallagher et al. 2001).

Future Research

Future research may proceed in several ways. First, it is still not clear how emotional trust and cognitive trust are different or similar in terms of their causes, formation processes, and consequences, and how to design an RA to promote emotional trust in the RA.

Second, it will be quite challenging to design a high-personalization RA, because customers' needs may be either explicit or implicit, or both. Possible methods include adaptive and dynamic interactions between an RA and a customer, or virtual trials.

Third, if emotional trust is measured in conjunction with other emotional responses to RAs (e.g., enjoyment and happiness), they may not covary, and they may have different effects on the intention to adopt. Future research needs to examine the relationships between emotional trust and other emotional reactions to an IT.

Fourth, the intention to adopt as a decision aid and the intention to adopt as a delegated agent may form a two-stage model, in which the use of an RA as a decision aid occurs before the RA is adopted as a delegated agent. Future research is needed to study the link between the two intentions to adopt, and the link between these intentions and actual customer behaviors.

Fifth, it is possible that familiarity serves as a moderator so that when a customer is more familiar with an RA, the impact of perceived personalization on cognitive trust may be more intense.

Finally, the results in this study imply that the behavioral intention to adopt an IT is not a purely cognitive process. It would be interesting to study emotional trust as part of the UTAUT model. The extended model might have more explanatory power, especially in the context of adopting personalized technologies in e-commerce, where the IT users are also online customers. For customers, trust and emotions are a necessary part of their decisions, including their decisions on IT acceptance and on the extent of their dependence on IT. Current IT acceptance models, such as UTAUT and TAM, are dominated by cognition, without paying enough attention to the role of emotions and trust. Having shown the important role of emotional trust in RA adoption, we hope to entice future researchers to incorporate both cognition and emotions in IT acceptance models, and further examine the related but potentially asymmetric roles of cognitive trust and emotional trust in IT acceptance.

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