Association for Information Systems
AIS Electronic Library (AISeL)

AMCIS 2004 Proceedings

Americas Conference on Information Systems (AMCIS)

December 2004

Trust and TAM for Online Recommendation Agents

Weiquan Wang
University of British Columbia

Izak Benbasat
University of British Columbia

Trust and TAM for Online Recommendation Agents

Weiquan Wang
Sauder School of Business,
University of British Columbia
2053 Main Mall, Vancouver, BC, V6T 1Z2
CANADA
wwang@sauder.ubc.ca

Izak Benbasat
Sauder School of Business,
University of British Columbia
2053 Main Mall, Vancouver, BC, V6T 1Z2
CANADA
benbasat@sauder.ubc.ca

ABSTRACT

Online product recommendation agents are becoming increasingly available on websites to assist consumers with reducing information overload, provide advice in finding suitable products, and facilitate online consumer decision-making. Central of these services is *consumer trust* in the agents.

In several recent studies, the trust construct has been successfully integrated into the Technology Adoption Model (TAM) for general online shopping environments where the websites are treated as an information technology and the e-vendors are treated as trust objects. This study extends the integrated Trust-TAM model to online recommendation agents. Such agents, unlike websites, are inherently more complex *personalized* technologies adapted to work on behalf of a principal (user). The relative importance of consumers' initial trust vis-à-vis other TAM use-antecedents was examined. Results indicate that consumers' initial trust not only directly influences their intention to adopt the agents but has indirect effect via their enhanced perceived usefulness of the agents.

Keywords

Trust, Technology Adoption Model (TAM), recommendation agents, online shopping.

INTRODUCTION

Rich customer service and support are the key factor that attracts consumers and keeps them royal to an online store (Reibstein, 2002). The proliferation and advances in the Internet-based technologies are providing many opportunities for online firms to better serve their customers. In particular, online recommendation agents are becoming increasingly available on websites to provide customers with shopping assistance. They help buyers and sellers reduce information overload (Maes, 1994) and improve decision quality (Haubl and Trifts, 2000). Acting on the customers' behalf, recommendation agents also provide shopping advice to customers (Maes, Guttman and Moukas, 1999); this advice is particularly helpful in relation to complex products. Without proper support, consumers may be limited in their ability to evaluate products since they cannot consult with salespeople as in a traditional shopping environment (Kim and Yoo, 2000). The challenge of choosing a complex product on the Web can be alleviated by an interface that guides and directs customer choices (Grenci and Todd, 2002). One type of such agents are content filtering-based product recommendation agents, which are defined as software entities that provide shopping advice on what to buy for consumers based on their needs and/or preferences (Ansari, Essegaier and Kohli, 2000). Such agent technologies, for example those provided by www.ActiveDecisions.com, have been successfully utilized in a variety of firms, including Yahoo! and Amazon.com, to provide value-added services for consumers.

However useful these recommendation agents are, central of these recommendation services is *consumer trust* in the agents. Users delegate a range of tasks to the agents that act on user's behalf. If users do not trust the agents, they would reject the recommendation and advice from the agents. Trust becomes more important in the online shopping environment due to the lack of proven guarantees that the e-vendors or the agent providers will not engage in harmful opportunistic behaviors and fewer cues that can be used to judge the quality of the recommendation services (Gefen, Karahanna and Straub, 2003b). Arguably, the effectiveness of recommendation agents depends on consumer's initial trust in them, and thus their use of the recommendation service.

In several recent studies, the trust construct has been successfully integrated into the Technology Adoption Model (TAM) for general online shopping environments where the websites are treated as an information technology (IT) and the e-vendors are treated as trust objects (Gefen, Karahanna and Straub, 2003a; Gefen et al., 2003b). This study extends the integrated Trust-

TAM model to online recommendation agents. Such agents, unlike websites, are inherently more complex *personalized* technologies which are adapted to work on behalf of a principal (user) by reflecting the specific needs and preferences of the principal. We intend to explore the relative importance of initial trust vis-à-vis other TAM use-antecedents in the adoption of online recommendation agents. In many prior empirical studies, simple technology adoption has been the focus of TAM, but a recent study by (Venkatesh, Morris, Davis and Davis, 2003), shows that TAM also holds for the complicated systems (e.g., sophisticated managerial systems).

LITERATURE REVIEW AND RESEARCH MODEL

Trust in Online Recommendation Agents

To an increasing degree, academics and practitioners have been recognizing trust as a key facilitator in eCommerce (Gefen et al., 2003b). Several comprehensive reviews of literature on trust studies have already been published (e.g., Mayer, Davis and Schoorman, 1995; McKnight, Choudhury and Kacmar, 2002; Gefen et al., 2003b) and thus this section only briefly describes trust in recommendation agents.

Based on the definitions of trust from Komiak and Benbasat (2003) and McKnight et al. (2002) , the current study defines trust in a recommendation agent as: one's beliefs in an agent's *competence*, *benevolence*, and *integrity*. According to McKnight et al. (2002), *competence-belief* means that one believes that the trustee has the ability, skills, and expertise to perform effectively in specific domains; *benevolence-belief* means that one believes that the trustee cares about one and acts in one's interest; and *integrity-belief* means that one believes that the trustee adheres to a set of principles (e.g., honesty and promise keeping) that one finds acceptable.

Our definition of trust in recommendation agents extends interpersonal trust to technological artifacts. Studies in human-computer interaction indicate that people treat computers as social actors and apply social rules to computers (e.g., Reeves and Nass, 1996). Reeves and Nass (1996), who have conducted more than 30 research studies on this issue, have found that even technologically sophisticated people treat technological artifacts (e.g., computers) as if they were other human beings, rather than tools only. They have provided ample evidence to support the treatment of technological artifacts as recipient of social relation of trust.

Several studies have also extended the trustees to abstract or technical systems including intelligent computer agents and indicated that some elements of human property (e.g., benevolence) can be assessed toward machines as well (Komiak and Benbasat, 2004; Muir and Moray, 1996). For example, studies by Muir and his collaborators (e.g., Muir, 1987; Muir and Moray, 1996) defined trust in machines and automation to include some morality dimension (e.g., responsibility). In a study of embodied conversational agents by (Cassell and Bickmore, 2000), trust is defined as a composite of benevolence and credibility. In another study, in order to understand the similarities and differences among human-human trust, trust in human-machine relationships, and trust in general, Jian, Bisantz and Drury (2000) have conducted a three-phase experiment, comprising a word elicitation study, a questionnaire study, and a paired comparison study. Their results have indicated that particular components of trust are similar across these three types of trust. Even for trust in machines, participants use words like "integrity", "honesty", "cruel", "harm", etc.

Initial Trust and TAM for Recommendation Agents

The Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980) is generally recognized as the best starting point for studying the determinants and effects of individuals' behavioral intentions including technology adoption (Sheppard, Hartwick and Warshaw, 1988). As the Internet and its related technologies are penetrating into our everyday life, the question is whether or not online buyers behave the same as off-line buyers. Given the importance of trust in online shopping environments, several recent studies by (Gefen et al., 2003a; Gefen et al., 2003b) have incorporated the construct of trust into the TAM, which is based on TRA, for general online shopping environments.

In a similar fashion, we hypothesize that trust plays an important role in predicting consumers' adoption intention of online recommendation agents. Such agents are inherently complex *personalized* technologies which are adapted to work on behalf of a principal (user) by reflecting the specific needs and preferences of the principal. An Internet-delivered agent is not owned exclusively by one user and there is an agency relationship between the agent and its users (Bergen and Dutta, 1992). Trust issues associated with recommendation agents are thus important and complicated since the user may have concerns about the *competence* of the agent in satisfying his needs, as well as being concerned about whether the agent is working on his behalf rather than on behalf of a web merchant or manufacture, that is, *integrity* and *benevolence* concerns. Consumers need to be relieved from these concerns when they consider adopting the recommendation agents. This is especially the case when consumers are new to the recommendation agents and they have limited interaction with the agents. Trust helps consumers rule out these undesirable concerns and encourage their adoption.

H_1: Initial trust in the online recommendation agents will positively affect intended adoption of the agents.

Trust should also increase the perceived usefulness (PU) of the recommendation agents. The PU is determined by at least two factors. One is the expected benefits (e.g. find a suitable product more efficiently and effectively) that users can get from the use of the agents (Gefen et al., 2003b) and the other is how much effort users need to invest in order to achieve the benefits (Davis, 1989). If the agents are not trustworthy because they do not have appropriate expertise in recommending products, work on behalf of the web merchant or manufacture without caring about the consumers, or is not honest, benefits from these agents are difficult to achieve and probably use of the agents are even detrimental. Therefore, the agents are less useful. The existence of the agency relationship between the agents and their consumers determines that such situations may occur and consumers' concerns regarding these issues are not rare given the potential harmful opportunistic behaviors and higher risks in the online environments (Gefen et al., 2003b).

Regarding the second determinant of PU, the impact of perceived ease-of-use (PEOU) on PU as described in TAM is well confirmed in many previous studies (e.g. Gefen, Straub and Boudreau, 2000).

H_2: Initial trust in the online recommendation agents will positively affect PU of the agents.

H_3: PEOU in the online recommendation agents will positively affect PU of the agents.

The integrated Trust-TAM model examined in Gefen et al. (2003b) also predicts that PEOU will increase trust. They argued that this impact is generated through the perception that the web merchant has invested efforts in the relationship with the consumers and by doing so, "signals a commitment to the relationship". This argument also applies to the online recommendation agents. Easy-to-use agents indicate that the agent providers care about users and invest in the commitment. Conversely, difficult-to-use agents may be perceived to be less capable and less considerate, and thus consumers may reduce their competence and benevolence beliefs in the agents.

H_4: PEOU in the online recommendation agents will positively affect trust in the agents.

Two important antecedents in the TAM are PU and PEOU. TAM also applies to more complicated technologies as demonstrated by previous studies (Venkatesh et al., 2003; Gentry and Calantone, 2002). The more useful and ease to use agents will be used more:

H_5: PU of the online recommendation agents affect intended adoption of the agents.

H_6: PEOU of the online recommendation agents affect intended adoption of the agents.

RESEARCH METHOD

Experimental Platform

To examine the integrated Trust-TAM model for online recommendation agents, a laboratory experiment was conducted. Simulating recommendation agents were built for experimental purpose. Building new agents rather than using those available in current websites is to ensure that all participants would be new to the agents and hence their initial trust in the agents would be examined. Our experimental agents were built to simulate those presented in other studies (Russo, 2002) and in leading commercial applications (e.g., www.ActiveDecisions.com and www.DealTime.com) though the interface of our agent is different from them. One of the most popular approaches to elicit consumer needs and preferences in choosing products is to use agent-user dialogues (Russo, 2002), where consumers answer several questions asked by recommendation agents regarding their needs and product preferences, and the agents provide shopping recommendations based on their answers. Figure 1 is a screen shot of the agent-user dialogue in an experimental platform developed for the current study, and Figure 2 gives an example of shopping recommendations arising from the agent-user dialogue. This simulating agent provides shopping advice for digital cameras. Different expected levels of trust, PU, and PEOU of the agents were created by providing different levels of explanation facilities in the agents. Explanation facilities have been proposed to be a critical component for any intelligent systems and be influential for these variables (Gregor and Benbasat, 1999; Hayes-Roth and Jacobstein, 1999).

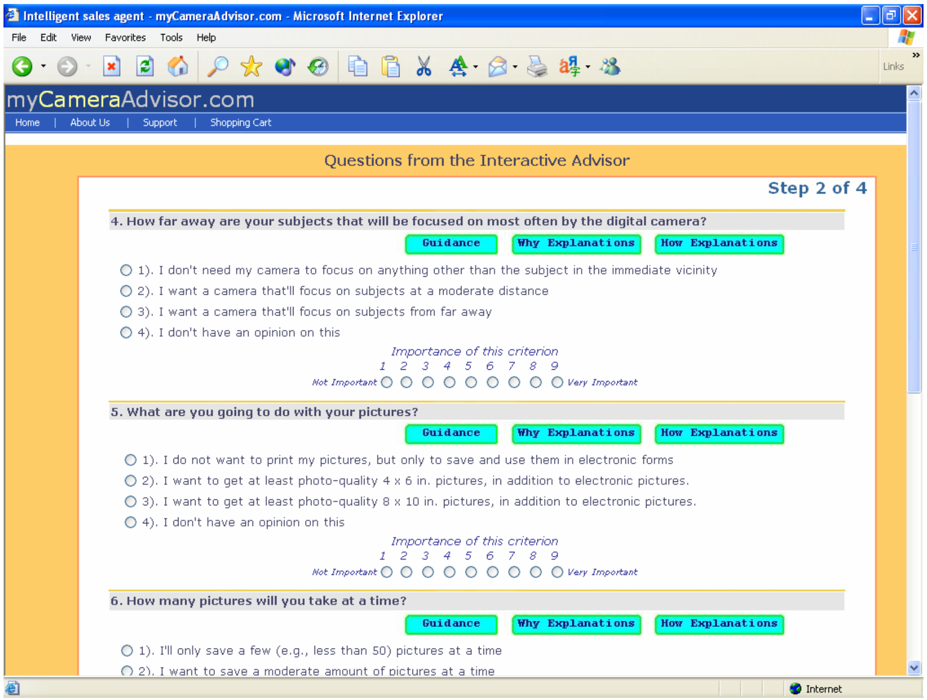

Figure 1. Agent-User Dialogue in the Experimental Agents

Figure 2. Recommendations from the Experimental Agents

Participants, Incentives, and Experimental Tasks and Procedures

A total of 120 students in a large North American university were recruited for the experiment. To avoid potential biases in their evaluations, only individuals who did not already own digital cameras were invited to participate in the study. This filtering is justified because most consumers may need extra shopping advice when they first buy a product like a digital camera and do not have sufficient relevant expertise and experience.

The experiment proceeded as follows. A research assistant first trained participants how to use and navigate the assigned Web interface. This tutorial agent had same features as the experimental agent. During the training section, no participants reported that they had used the agents before. Then, each participant was asked to finish two tasks, first choosing a digital camera for a good friend and then selecting another camera for a close family member. The order of the two tasks is counter-balanced. After each task, the participants were directed to an online form to write down their choice and its justifications. There was no time limit for the tasks. Two tasks were used instead of one in order to ensure that participants have sufficient interactions to make judgments about the agent[1]. Finally, after the two tasks, participants were asked to complete a questionnaire including the measures of dependent variables.

Each participant was guaranteed a small monetary compensation for their participation ($15), and in order to motivate participants to view the experiment as a serious online shopping session and to increase their involvement, the top 25% performers were offered an extra amount ($25), and the participant with the best performance would be offered $200. The main criterion for the performance is based on the extent to which their justifications are appropriate and convincing to support their choice of digital cameras.

Measures

This study used existing validated scales for all constructs. All items were set in a nine-point scale ranging from Strongly Disagree (1) to Strongly Agree (9). Measures for PU, PEOU, and intention to adopt have been adapted from Davis's scale (Davis, 1989), and measures for trust were developed and validated by (Komiak and Benbasat, 2003). All measurement items are listed in the Appendix. The means and standard deviations of all measured constructs are reported in Table 1.

Variable	Mean	s.d.	Composite Reliability	Cronbach Alpha	1	2	3	4	5	6
1. Competence	5.55	1.39	.89	.85	**.79**[a]					
2. Benevolence	6.18	1.29	.87	.77	.65**	**.84**				
3. Integrity	6.04	1.21	.86	.75	.34**	.51**	**.82**			
4. PU	5.68	1.06	.93	.90	.70**	.48**	.36**	**.90**		
5. PEOU	6.88	1.02	.83	.73	.59**	.48**	.46**	.42**	**.70**	
6. Intention to Adopt	7.03	1.29	.93	.89	.48**	.46**	.21*	.54**	.42**	**.76**

Table 1 Construct Attributes

a: Diagonal elements are square roots of the average variance extracted (AVE) and off-diagonal elements are inter-construct correlations.

** and * indicate the correlations are significant at the .01 and .05 level, respectively.

RESULTS

Partial Least Squares (PLS), as implemented in PLS Graph version 3.0, was used for data analysis[2].

Data Analysis for the Measurement Model

Trust is modeled as a reflective second order factor (McKnight et al., 2002) and it is composed of three sub-constructs (i.e., competence, benevolence, and integrity) which are reflective as well. As suggested by (Chin, 2000), in PLS, all measures for the first order trusting beliefs were repeated for the second order trust construct.

---

[1] Our pilot test showed that many participants were not very confident in evaluating the agent after completing only one task. After two tasks, participants' evaluations of the recommendation agents reached a relatively stable level and they had no difficulties in answering the questionnaire.

[2] The main reason we choose PLS is because of its minimal demands on sample size and residual distribution (Barclay et al., 1995).

To assess the reliability (individual item reliability and internal consistency) and validity, the item loadings, composite reliability of constructs, and average variance extracted (AVE) were reported. All of the reflective constructs and sub-constructs displayed strongly positive loadings and high levels of statistical significance for all items (see Table 2), indicating high individual item reliability[3]. All composite reliabilities and Cronbach's alphas in Table 1 are greater than .70, which is considered as a benchmark for acceptable reliability (Barclay, Thompson and Higgins, 1995). The AVE, and it should be greater than .50 to justify using a construct (Barclay et al., 1995). Adequate AVEs for all three constructs are indicated in Table 1.

Two criteria were suggested by (Barclay et al., 1995) to examine discriminant validity. One criterion for adequate discriminant validity is that the square root of each construct's AVE is greater than the correlations between the construct and others. This criterion is satisfied as shown in Table 1. A second criterion is that no item loads more highly on another construct than it does on the construct it intends to measure. The factor and cross-loadings reported in Table 2 demonstrated adequate discriminant validity[4].

Items	**Competence (CMPT)**	**Benevolence (BNVL)**	**Integrity (INTG)**	**Perceived Usefulness (PU)**	**Perceived Ease of Use (PEOU)**	**Intention to Adopt (INTN)**
CMPT1	**.83*****	.48	.31	.59	.52	.38
CMPT2	**.89*****	.54	.22	.55	.43	.32
CMPT3	**.76*****	.39	.25	.58	.45	.40
CMPT4	**.76*****	.61	.22	.51	.44	.38
CMPT5	**.71*****	.57	.35	.58	.57	.44
BNVL1	.57	**.86*****	.46	.47	.42	.50
BNVL2	.57	**.89*****	.44	.41	.46	.40
BNVL3	.50	**.75*****	.37	.34	.36	.25
INTG1	.31	.44	**.78*****	.29	.34	.26
INTG2	.26	.40	**.87*****	.27	.33	.12
INTG3	.26	.41	**.81*****	.35	.46	.12
PU1	.57	.35	.24	**.78*****	.50	.57
PU2	.53	.43	.35	**.78*****	.60	.56
PU3	.58	.44	.32	**.84*****	.62	.47
PU4	.60	.37	.25	**.86*****	.64	.48
PU5	.47	.35	.23	**.66*****	.62	.28
PU6	.42	.23	.23	**.68*****	.47	.25
PU7	.50	.33	.36	**.65*****	.45	.25
PU8	.50	.38	.23	**.70*****	.52	.38
PU9	.65	.46	.32	**.88*****	.67	.60
PEOU1	.51	.36	.36	.55	**.76*****	.35
PEOU2	.27	.24	.23	.32	**.64*****	.35
PEOU3	.34	.33	.33	.44	**.66*****	.11
PEOU4	.55	.44	.32	.73	**.73*****	.46
PEOU5	.33	.31	.38	.41	**.74*****	.27
INTN1	.43	.51	.19	.45	.37	**.91*****
INTN2	.47	.42	.19	.58	.46	**.93*****
INTN3	.40	.42	.19	.52	.41	**.89*****

Table 2 Factor Loadings and Cross-Loadings

*** indicate significant in the .001 level.

---

[3] A rule of thumb suggested by (Barclay et al. 1995) is to require items with loadings of .7 or more. Several items in PU and PEOU do not satisfy this criterion. The drop of these items engenders very little changes in the path values and no changes in significant levels in the structural model. Because these measures have been firmly established by previous studies, all items were used for data analysis in the current study.

[4] There are some exceptions in perceived usefulness and ease of use. Again, the drop of some items engenders very little changes in the path values and no changes in significant levels in the structural model and they were kept for data analysis.

Data Analysis for the Structural Model

The results of the structural model from PLS including path coefficients, explained variances, and significant levels, are shown in Figure 3. The total effects of three antecedents as well as their direct and indirect effects are reported in Table 3.

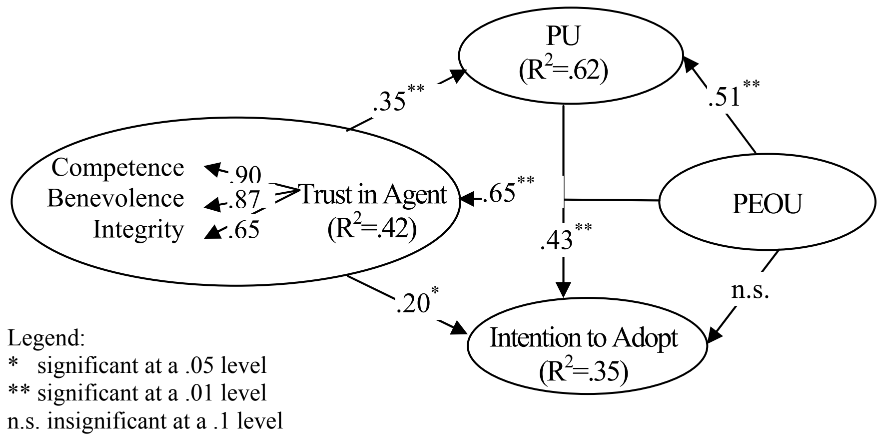

Figure 3. PLS Results

Hypothesis	**Standardized Path Coefficient (direct effect)**	**t-value for Path**	**Indirect Effect**	**Total Effect[a]**
H1: Trust → Adoption Intention	.20	2.19	.15	.35
H2: Trust → PU	.35	5.76	--	.35
H3: PEOU → PU	.51	7.39	.23	.84
H4: PEOU → Trust	.65	9.54	--	.65
H5: PU → Adoption Intention	.43	2.95	--	.43
H6: PEOU → Adoption Intention	--	--	.35	.35

Table 3 Structural Model Results

a: Total Effect = Direct Effect + Indirect Effect.

The analysis indicates that most of the hypotheses were supported. Consumers' initial trust and PU have significant impact on their intention to adopt the agents while PEOU does not. Therefore, H_1 and H_5 were supported while H_6 not. Both consumers' initial trust and PEOU significantly influence their PU of the agents and thus H_2 and H_3 were supported. PEOU also significantly influence consumers' trust in the agents and thus H_4 was supported. Consumers' initial trust not only directly influences their intention to adopt the recommendation agents but also have indirect effect through their increased PU of the agent. This result is similar to (Gefen et al., 2003a) though they did not examine the indirect impact. The impact of PEOU on intention to adopt is fully mediated by PU and trust. This finding is not unusual because many other TAM studies (e.g. Davis, 1989) have found PEOU is mediated by PU and Gefen et al. (2003a) have also found that PEOU is mediated by trust though their finding is for experienced consumers.

Results in Table 4 indicate that PU has the strongest impact on intention to adopt in terms of both direct and total effect. This is different from Gefen et al. (2003a) where they found that for new customers only trust influence purchase intention while PU does not. The total effects of trust and PEOU on intention to adopt are the same but trust have both direct effect and indirect effect while PEOU only has indirect effect. The variance of adoption intention explained by trust, PU, and PEOU in this model is 35 percentages, which is relatively high compared with Gefen et al. (2003a).

CONCLUSION AND DISCUSSION

Consumers' initial trust plays an important role in their decision to adopt online recommendation agents. This study provides similar results as other trust and TAM studies in general. However, different from Gefen et al. (2003a), we found that for new users, both trust and PU have direct effect on their adoption intention while PEOU influences trust and PU. Even for new customers, PU remains the most important predictor of adoption intention, as in many previous TAM studies. Meanwhile, trust and PEOU are important factors that increase PU of the agents. Therefore, to increase the effectiveness of online recommendation agents, designers should build the agents to be more easy to use, trustworthy, and useful. Much more research effort should be invested in these aspects. For example, a trustworthy agent may need to be embedded with a set of appropriate explanation facilities (Wang and Benbasat, 2003), and to be personalized with better understanding of users' real needs (Komiak and Benbasat, 2003).

There are some methodology issues that need to be addressed. The potential for common method variance may exist because measures of all constructs in this study were collected at the same time point and via the same instrument (Straub, Limayem and Karahanna-Evaristo, 1995). In addition, university student participants were participated in this study. More replications to test our model in other populations are needed to examine the external validity of our findings. Our results were based on only one type of recommendation agent. Readers are advised to be cautious to generalize the results of this study to other types of recommendation agents.

REFERENCES

1. Ajzen, I. and Fishbein, M. (1980) Understanding Attitudes and Predicting Social Behaviour, Prentice Hall.
2. Ansari, A., Essegaier, S. and Kohli, R. (2000) Internet Recommendation Systems, *Journal of Marketing Research*, 37, 3, 363-375.
3. Barclay, D., Thompson, R. and Higgins, C. (1995) The Partial Least Squares (PLS) Approach to Causal Modeling: Personal Computer Adoption and Use as an Illustration, *Technology Studies*, 2, 2, 285-309.
4. Bergen, M. and Dutta, S. (1992) Agency Relationships in Marketing: A Review of the Implications and Applications of Agency and Related Theories, *Journal of Marketing*, 56, 3, 1-24.
5. Cassell, J. and Bickmore, T. (2000) External Manifestation of Trustworthiness in the Interface, *Communications of the ACM*, 43, 12, 50-56.
6. Chin, W. W. (2000) Partial Least Squares For Researchers: An Overview and Presentation of Recent Advances Using the PLS Approach, ICIS 2000 tutorial on PLS, Online available at: http://disc-nt.cba.uh.edu/chin/icis2000plstalk.pdf.
7. Davis, F. D. (1989) Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology, *MIS Quarterly*, 13, 3, 319-340.
8. Gefen, D., Karahanna, E. and Straub, D. W. (2003a) Inexperience and Experience With Online Stores: The Importance of TAM and Trust, *IEEE Transactions On Engineering Management*, 50, 3, 307-321.
9. Gefen, D., Karahanna, E. and Straub, D. W. (2003b) Trust and TAM in Online Shopping: An Integrated Model, *MIS Quarterly*, 27, 1, 51-90.
10. Gefen, D., Straub, D. W. and Boudreau, M. C. (2000) Structural Equation Modeling and Regression: Guidelines for Research Practice, *Communications of the Association for Information Systems*, 4, 7
11. Gentry, L. and Calantone, R. (2002) A Comparison of Three Models to Explain Shop-Bot Use on the Web, *Psychology and Marketing*, 19, 11, 945 -956.
12. Gregor, S. and Benbasat, I. (1999) Explanations from Intelligent Systems: Theoretical Foundations and Implications For Practice, *MIS Quarterly*, 23, 4, 497-530.
13. Grenci, R. T. and Todd, P. A. (2002) Solutions-Driven Marketing, *Communications of the ACM*, 45, 3, 65-71.
14. Haubl, G. and Trifts, V. (2000) Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids, *Marketing Science*, 19, 1, 4-21.
15. Hayes-Roth, F. and Jacobstein, N. (1999) The State of Knowledge-Based Systems, *Communications of the ACM*, 37, 4, 27-39.
16. Jian, J. Y., Bisantz, A. M. and Drury, C. G. (2000) Foundations for an Empirically Determined Scale of Trust in Automated Systems, *International Journal of Cognitive Ergonomics*, 4, 1, 53-71.

17. Kim, J. and Yoo, B. (2000) Toward the Optimal Link Structure of the Cyber Shopping Mall, *International Journal of Human-Computer Studies*, 52, 3, 531-551.
18. Komiak, X. S. and Benbasat, I. (2003) The Impact of Internalization and Familiarity on Trust and Adoption of Recommendation Agents, *Working Paper 02-MIS-006*, MIS Division, University of British Columbia, Vancouver, Canada.
19. Komiak, X. S. and Benbasat, I. (2004) Understanding Customer Trust in Agent-mediated Electronic Commerce, Web-mediated Electronic Commerce, and Traditional Commerce, *Information Technology and Management (ITM)*, 5, 1&2, 181-207.
20. Maes, P. (1994) Agents that Reduce Work and Information Overload, *Communications of the ACM*, 37, 7, 31-40.
21. Maes, P., Guttman, R. H. and Moukas, A. G. (1999) Agents that Buy and Sell, *Communications of the ACM*, 42, 3, 81-91.
22. Mayer, R. C., Davis, J. H. and Schoorman, F. D. (1995) An Integrative Model of Organizational Trust, *Academy of Management Review*, 20, 3, 709-734.
23. McKnight, D. H., Choudhury, V. and Kacmar, C. (2002) Developing and Validating Trust Measures for e-Commerce: An Integrative Typology, *Information Systems Research*, 13, 3, 334-359.
24. Muir, B. M. (1987) Trust Between Humans and Machines, and the Design of Decision Aids, *International Journal of Man Machine Studies*, 27, 5-6, 527-539.
25. Muir, B. M. and Moray, N. (1996) Trust in Automation: Part II. Experimental Studies of Trust and Human Intervention in a Process Control Simulation, *Ergonomics*, 39, 3, 429-460.
26. Reeves, B. and Nass, C. (1996) The Media Equation: How People Treat Computers, Television, and New Media Like Real People and Places, Cambridge University Press, New York, NY.
27. Reibstein, D. J. (2002) What Attracts Customers to Online Stores, and What Keeps Them Coming Back?, *Journal of the Academy of Marketing Science*, 30, 4, 465-473.
28. Russo, J. E. (2002) Aiding Purchase Decisions on the Internet, in *Proceedings of the Winter 2002 SSGRR International Conference on Advances in Infrastructure for Electronic Business, Education, Science, and Medicine on the Internet*, Milutinovic, V. (ed.), Italy.
29. Sheppard, B. H., Hartwick, J. and Warshaw, P. R. (1988) The theory of reasoned action: a meta-analysis of past research with recommendations for modifications and future research, *Journal of Consumer Research*, 15, 3, 325-343.
30. Straub, D., Limayem, M. and Karahanna-Evaristo, E. (1995) Measuring System Usage: Implications for IS Theory Testing, *Management Science*, 41, 8, 1328-1342.
31. Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003) User Acceptance of Information Technology: Toward a Unified View, *MIS Quarterly*, 27, 3, 425-478.
32. Wang, W. and Benbasat, I. (2003) An Empirical Investigation of Intelligent Agents for E-Business Customer Relationship Management: A Knowledge Management Perspective, in The *Proceedings of the 11th European Conference on Information Systems*, Naples, Italy.

APPENDIX: MEASUREMENT ITEMS

Trust – Competence

1. This virtual advisor[5] is like a real expert in assessing digital cameras.
2. This virtual advisor has the expertise to understand my needs and preferences about digital cameras.
3. This virtual advisor has the ability to understand my needs and preferences about digital cameras.
4. This virtual advisor has good knowledge about digital cameras.
5. This virtual advisor considers my needs and all important attributes of digital cameras.

Trust – Benevolence

1. This virtual advisor puts my interest first.
2. This virtual advisor keeps my interests in its mind.
3. This virtual advisor wants to understand my needs and preferences.

Trust – Integrity

1. This virtual advisor provides unbiased product recommendations.
2. This virtual advisor is honest.
3. I consider this virtual advisor to be of integrity.

PU

1. Using this virtual advisor enabled me to find suitable digital cameras more quickly.
2. Using this virtual advisor improved the quality of analysis/search I performed to find suitable digital cameras.
3. Using this virtual advisor made the search task for digital cameras easier to do.
4. Using this virtual advisor enhanced my effectiveness in finding suitable digital cameras.
5. Using this virtual advisor gave me more control over the digital camera search task.
6. Using this virtual advisor allowed me to accomplish more analysis than would otherwise have been possible.
7. Using this virtual advisor greatly enhanced the quality of my judgments.
8. Using this virtual advisor conveniently supported all the various types of analysis needed to find suitable digital cameras.
9. Overall, I found this virtual advisor useful in finding suitable digital cameras.

PEOU

1. My interaction with the virtual advisor is clear and understandable.
2. It is easy to get the virtual advisor to do what I want to do.
3. Learning to use the virtual advisor is easy to me.
4. It was easy for me to find a suitable digital camera using the virtual advisor.
5. Overall, I found that the virtual advisor is easy to use.

Intention to Adopt

1. I am willing to use this virtual advisor as an aid to help with my decision about which product to buy.
2. I am willing to let this virtual advisor assist me in deciding which product to buy.
3. I am willing to use this virtual advisor as a tool that suggests to me a number of products from which I can choose.

[5] We use the word “virtual advisor” to refer to the recommendation agent since in our pilot test, participants suggested that using the word “virtual advisor” is easier to understand than “recommendation agent”.