DESIGN OF TRUSTWORTHY ONLINE RECOMMENDATION AGENTS:

EXPLANATION FACILITIES AND DECISION STRATEGY SUPPORT

by

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A THESIS SUBMITTED IN PARTIAL FULFILMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

THE FACULTY OF GRADUATE STUDIES

(Business Administration)

THE UNIVERSITY OF BRITISH COLUMBIA

September 2005

ABSTRACT

Due to advances in Web-based technologies, ample opportunities exist to utilize knowledge-based systems for facilitating online consumer decision-making and for providing recommendation services for consumers. This thesis focuses on online recommendation agents that offer shopping advice based on user-specified needs and preferences. Because of the high risks and uncertainties inherent in online environments, effective recommendation agents need to be trustworthy. By extending interpersonal trust to trust in technological artifacts, consumers' trust in a recommendation agent is defined to include three belief components: *competence*, *benevolence*, and *integrity*.

This thesis examines user acceptance of online recommendation agents and trust formation in the agents and it empirically investigates agent features and capabilities that increase the trust in them so that a higher chance of user acceptance can be realized. Two important agent capabilities are tested: 1) explanation facilities and 2) decision strategy support.

An integrated Trust-TAM (Technology Acceptance Model) was tested and the results show that trust in agents influences consumers' behavioral intentions. Trust in agents exerts a direct impact on the intentions to adopt recommendation agents as well as an indirect impact via the perceived usefulness of the agents.

Written protocols were collected and analyzed to identify the major processes that build and inhibit consumers' trust in recommendation agents. The results highlight the important roles of several processes in cultivating and inhibiting agent trust, such as expectation confirmation, utility assessment, and information sharing.

Regarding explanation facilities, this research tests three types of explanations – *how* explanations, *why* explanations, and *guidance*. The results indicate that the use of different types of explanations increases different trusting beliefs: the use of *how* explanations increases competence and benevolence beliefs; the use of *why* explanations increases the benevolence belief; and the use of *guidance* increases the integrity belief.

The impact of decision strategy support on consumers' trust and adoption of online recommendation agents was also investigated together with explanation facilities.

Three types of recommendation agents with different levels of decision strategy support were compared. Both the benefits and costs of providing a high level of decision strategy support were examined. The results suggest that recommendation agents with decision strategy support capabilities and explanation facilities deliver benefits to users (e.g., more useful and trustworthy) and have a higher chance of being adopted by users, when the use of the agents does not require much additional effort.

This research has addressed an important gap that exists in our current understanding of trustworthy online recommendation agents. It also makes a key contribution by empirically testing the effects of explanation facilities and decision strategy support on consumers' trust and acceptance of online recommendation agents.

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CHAPTER 1: INTRODUCTION

Good customer service and support are the key factors that attract consumers and keep them loyal to an online store (Reibstein, 2002). Currently, with the proliferation and advances of Web-based technologies, many opportunities are being created 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 (Rust and Kannan, 2003), to help buyers and sellers reduce information overload (Maes, 1994), and to improve consumers' decision quality (Haubl and Trifts, 2000). Acting on behalf of consumers, recommendation agents provide advice to assist in shopping activities (Maes et al., 1999). Without the proper support, consumers may be limited in their abilities to evaluate products, inasmuch as they cannot consult with salespeople as they can in conventional shopping environments (Kim and Yoo, 2000). Thus, the challenge of choosing a product on the Web can be alleviated by an interface with a recommendation agent that informs and directs customer choices (Grenci and Todd, 2002).

This dissertation focuses on an important but under-studied type of agents: *content-filtering product recommendation agents* (Ansari et al., 2000; Maes et al., 1999). They are software entities that carry out some set of operations on behalf of consumers, and provide shopping advice about the product(s) consumers should purchase, based on their needs and preferences (Ansari et al., 2000). Such agent technologies, for example, those provided by www.ActiveDecisions.com and www.myProductAdvisor.com, have been utilized to provide value-added services for consumers in a variety of firms, including Yahoo! and Amazon.com.

Nevertheless, a survey conducted by Burke (2002) shows that a significant percentage (21%) of online shoppers have negative reactions towards such recommendation services. Consequently, the need has been expressed to investigate the designs that lead to more effective agent technologies for e-commerce. One important factor that has emerged in electronic environments is consumer trust in online recommendation agents. Since consumers delegate a range of tasks to the agents that act

on their behalf, if a consumer does not trust the agent, the recommendations and advice will likely be rejected. Moreover, trust is becoming increasingly important in online shopping environments because of the possibility that e-vendors or agent providers might engage in opportunistic behaviors (e.g., by taking advantage of consumers and providing biased recommendations), and the lack of cues available to assess the quality of recommendation services (Gefen et al., 2003b). In a focus group experiment, Andersen, Hansen and Andersen (2001) found that trust in recommendation agents is the most important expectation users have.

Nevertheless, trust in online recommendation agents remains an under-investigated area. Previous trust studies have mainly focused on interpersonal and organizational trust. Few studies have examined the role of agent trust in users' acceptance of recommendation agents, the formation processes of trust in the agents, or agent capabilities that can enhance consumers' trust in the agents.

1.1 Research Objective and Questions

The main objective of this research is to study consumers' acceptance of online recommendation agents and their trust formation in the agents, and to empirically investigate agent features and capabilities that can increase trust in recommendation agents and lead to a higher chance of agent acceptance.

In this dissertation, two important agent capabilities are examined: 1) explanation facilities and 2) decision strategy support. The ability to explain knowledge and reasoning, referred to as explanation facilities, is a critical component of intelligent systems, including recommendation agents. By virtue of making the performance of a system transparent to users, user trust is promoted and user acceptance of the system is influenced (Gregor and Benbasat, 1999; Hayes-Roth and Jacobstein, 1994). Nevertheless, few studies have empirically tested the impact of explanation facilities on consumers' trust in recommendation agents.

Online recommendation agents help consumers reduce information overload and improve decision quality (e.g., Haubl and Trifts, 2000; Maes, 1994), but also restrict consumers to certain decision processes that are supported by the agents (Silver, 1990). Due to the large number of product alternatives that are available in an online store or across a variety of online stores, the decision strategy supported by an agent must be able to effectively narrow down the product alternatives and retain the products that are most suitable for consumers. Accordingly, the design of decision strategy support is a challenging issue for online recommendation agents. The findings reported in this thesis point for more user control and choice of agent strategies so that agents can be less restrictive and better able to cater to consumers' strategy preferences. As a result, the agents become more trustworthy and useful.

In this dissertation, we extend interpersonal trust to trust in technological artifacts, and define trust in online recommendation agents to include three belief components: *competence*, *benevolence*, and *integrity* (Komiak, 2003; McKnight et al., 2002a). *Competence-belief* means that an individual believes that the agent has the ability, skills, and expertise to perform effectively in specific domains; *benevolence-belief* means that an individual believes that the agent cares about and acts in the individual's interests; and *integrity-belief* means that an individual believes that the agent adheres to a set of principles (e.g., honesty and promise keeping) that are acceptable to the individual.

In particular, this thesis examines the following questions:

1) What is the nature of trust in online recommendation agents? How important is trust in agents vis-à-vis other antecedents of agent adoption (i.e., perceived usefulness and perceived ease-of-use of agents)?

2) How do consumers form trust in online recommendation agents? What are the most powerful building and inhibiting processes?

3) What types of explanations should be embedded in online recommendation agents? Does the use of explanations influence consumers' trust in agents? If so, how, and to what extent?

4) Does a high level of decision strategy support that allows user control and choice of decision strategy influence consumers' trust or other perceptions that lead to user adoption of recommendation agents? If so, how, and to what extent? What is the role of explanations in providing decision strategy support?

1.2 Method and Main Findings

To investigate the above research questions, two laboratory experiments were conducted. Experiment 1 is aimed at addressing the first three questions. Different types of explanations were manipulated to test their differential roles in increasing consumers' trust. To examine the nomological validity of trust in recommendation agents and user acceptance of the agents, the TAM (Technology Acceptance Model) is extended with the construct of trust in agents, and relevant user perceptions and intentions were surveyed in the experiment. At the end of the experiment, participants were also asked to justify their trust levels in the recommendation agents. Their justifications were analyzed to understand the major processes that build or inhibit agent trust.

The fourth question is addressed in Experiment 2. Different levels of decision strategy support were implemented in three types of agents supporting different choice strategies. Both the benefits and the costs of the decision strategy support capabilities were investigated. Explanation facilities were manipulated to examine the relative importance of the two agent capabilities (i.e., decision strategy support and explanation facilities) as well as their joint effects on users' perceptions and evaluations of the agents. In addition, this study investigated important variables that mediate the impact of the two agent capabilities on the antecedents of users' adoption of an agent.

The major findings of the two experiments are summarized as follows:

- Trust in agents influences consumers' behavioral intentions, exerting a direct impact on intentions to adopt recommendation agents as well as an indirect impact via perceived usefulness of the agents.

- Overall, consumers' expectations, utility assessment, and knowledge about an agent were the most important processes influencing their trust levels in the agent. Further, different trusting beliefs are formed via different processes. Also, different processes are involved in increasing or decreasing a trusting belief, indicating an asymmetric structure of trust building and trust inhibiting.

- Explanation facilities play an important role in enhancing trust in online recommendation agents. The use of different types of explanations increases different trusting beliefs: the use of *how* explanations increases consumers' beliefs in agent competence and benevolence, the use of *why* explanations increases consumers' beliefs in agent benevolence, and the use of *guidance* increases consumers' beliefs in agent integrity.

- Decision strategy support, implemented via user control and user choice of decision strategies, influences perceived agent strategy restrictiveness, which has an impact on consumers' trust and perceived usefulness of an agent. Explanation facilities influence trust in the agent by improving perceived agent transparency.

- Explanations should accompany the provision of decision strategy support capabilities so that consumers can easily understand the capabilities and be able to apply them properly. As well, the decision strategy support capabilities provided by an agent will not be effective unless the cognitive effort in learning and using the capabilities is low.

1.3 Structure of the Thesis

The remainder of the thesis is structured as follows. Chapter 2 reviews the literature on online recommendation agents. The nature of trust in technological artifacts is also discussed and trust in online recommendation agents is defined.

Chapter 3 focuses on the impact of explanation facilities on consumers' trust in online recommendation agents. Three types of explanations are investigated: *how* explanations, *why* explanations, and *guidance*. *How* explanations reveal the line of reasoning used by agents, on the basis of consumer needs and product preferences, and they outline the logical processes involved in reaching final recommendations. *Why* explanations justify the importance and purpose of agents' questions to consumers, in addition to providing justifications for the recommendations provided after the consultation is complete. *Guidance* provides objective knowledge regarding the potential constraints brought about by different choices for the questions in the agent-user dialogue. The different effects of the three types of explanations on different trusting beliefs are examined utilizing an analysis of covariance.

In chapter 4, an integrated Trust-TAM is tested to understand user acceptance of online recommendation agents and reveal the relative importance of trust vis-à-vis other antecedents of intentions to adopt recommendation agents. A Partial Least Squares analysis is applied to test the structural model.

In chapter 5, the written protocols that are used by participants to justify their trust levels in recommendation agents are analyzed. Based on prior research and the written protocols, an agent trust formation scheme, including 12 processes, are developed to code the written protocols. The major processes that build and inhibit different trusting beliefs are identified from the protocol analysis, and they are further quantitatively analyzed to predict participants' trusting beliefs.

Chapter 6 tests the impact of decision strategy support on consumers' trust and adoption of online recommendation agents, together with explanation facilities. Three types of recommendation agents, with different levels of decision strategy support, were

compared. The role of explanations in realizing the benefits of high decision strategy support is also investigated. To further understand the impact of explanations on trust, the mediating role of perceived agent transparency is examined. This chapter covers both the impact of decision strategy support and explanations on user perceptions, individually and jointly, and the consequence of these perceptions (i.e., behavioral intentions).

Finally, chapter 7 summarizes the studies conducted, outlines the major contributions of this research, and provides suggestions for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter first reviews previous research in the area of recommendation agents and identifies a research gap – design of trustworthy online recommendation agents with explanation facilities and decision strategy support. Then, these two agent features and capabilities that are examined in this dissertation are briefly discussed in sections 2.2 and 2.3. Section 2.4 discusses the nature of trust in technological artifacts and online recommendation agents, and section 2.5 defines trust in recommendation agents.

2.1 Prior Studies on Recommendation Agents

Web-based intelligent recommendation agents have been the focus of research for many years. Much research has been being conducted due to the wide applications of recommendation agents in online environments. Table 2-1 summarizes the prior studies that have examined the impact of recommendation agents and their various features and capabilities.

Table 2-1 Prior Agent Studies					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
Impact of Agents	*Häubl and Trifts (2000)*	• Recommendation Agent (RA) • Comparison Matrix (CM)	• Amount of search for product information • Consideration set size and quality • Decision Quality (purchase a non-dominated alternative, switch to another alternative, and degree of confidence)	N/A	• RA increases consumer decision quality, reduces the amount of information search and consideration set size, and increases consideration set quality. • CM reduces consideration set size and increases consideration set quality.
	Häubl and Murray (2003)	• Recommendation Agent (RA)	• Consumers' preference construction • Preference persistence	N/A	• The inclusion of an attribute in a RA renders this attribute more prominent. • The preference-construction effect persists beyond initial shopping experience.
	Urban et al (1999)	• Virtual Advisor (VA) • Information intensive site	• Trust • Intentions to use the VA • Willingness to pay for the recommendation service	N/A	• VA increases consumer trust in the website. • Most consumers would be willing to pay for the service. • Half participants prefer the VA site while the other half prefer the information intensive site.
	Lai and Yang (2000)	• Five types of browsing agents: recommendation agent, new-content agent, search agent, customized agent, and personal-status agent	Only the customized agents were evaluated: • Effectiveness (number of preferred products) and efficiency (number of clicks) • User satisfaction	N/A	• The customized agents increase the browsing effectiveness and efficiency and user satisfaction.
	Choi et al (2001)	• Anthropomorphic agent (AA)	• Telepresence • Social presence • Attitude towards ads and brand • Intentions to revisit the website and to purchase	N/A	• Ads with an AA generate higher telepresence and social presence than ads without the agent. • People who are exposed to the ads with an agent have more favorable attitude toward the ads and have a higher intention to revisit the website.

Table 2-1 Prior Agent Studies (cont'd)					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
Different Types of Agents	*Ansari et al (2000)*	• Bayesian based recommendation agent (BSRA) • Collaborative filtering based recommendation agents (CFRA)	• Marginal Likelihood of data • Deviance information criterion • Predictive ability	• Customer heterogeneity • Movie heterogeneity	• BSRA has better predictive power than CFRA. • BSRA can even make recommendations when CFRA cannot.
	Lee et al (2002)	• Agent types (profile based vs. self-expressed preference based) • Product types (frequently purchased commodity vs. less frequently purchased products)	• Preference accuracy • Ability to adapt to consumer preference changes	N/A	• The two agents have better performance compared with the benchmark method (k-NN method) for the two types of products respectively.
User-Agent Dialogue Design	*Komiak (2003)*	• Needs-based vs. attribute-based dialogues	• Internalization • Trust (cognitive and emotional) • Intentions to adopt agents as decision aids and to delegate shopping decisions to the agents	N/A	• Needs-based dialogues increase consumers' perceived internalization of the agents, which increase their cognitive trust in the agents. • Cognitive trust influence s consumers' intentions to adopt the agents as decision aids and this effect is fully mediated by their emotional trust in the agents.
	Norman (1994)	• N/A (General discussion)	N/A	N/A	• Provide a general discussion on user-agent interaction forms and other issues
Preference Elicitation	*Aggarwal and Vaidyanathan (2003)*	• Conjoint-type full-profile ratings • Self-explicated ratings	• Product attribute preference ranking and weights	N/A	• A mismatch was found between these two methods.
	Olson and Widing II (2002)	• Interactive Agents (user-inputted attribute importance weights) vs. passive agents (equal weights)	• Decision quality • Liking of the agent • Decision-making time	N/A	• Passive agents perform as well as or even better than the interactive agents on all the dependent variables.
	Moon (2000)	• Reciprocity • Sequence	• Willingness to reveal intimate information	N/A	• Subjects were more willing to reveal intimate information in the reciprocal and gradual conditions.

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Table 2-1 Prior Agent Studies (cont'd)					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
Explanation Facilities	*Sinha and Swearingen (2002)*	• Perceived transparency of collaborative recommender systems	• Liking of the system • Confidence in the recommendations	N/A	• Users like and feel more confident about recommendations that they perceived more transparent.
	Herlocker et al (2000)	• Explanations	• Filtering performance of the system • User acceptance of the system	N/A	• 86% of survey respondents preferred the systems with explanations. • Filtering performance could not be evaluated due to their research design.
Strategy Design	*Tan (2003)*	• Hyperlink-based aid • Attribute-screen aid • Weight-attribute-screen aid • Sorting aid	• Decision accuracy • Consideration time • Consideration set quality • Consideration set size	• Information load	• More sophisticated aids reduce cognitive effort but do not increase decision quality • The impact on decision quality depends on the information load
	Pereira (2000)	• Search strategy (elimination by aspect, weighted average method, profile building, and simple hypertext) • Product class knowledge	• Satisfaction in the decision process • Confidence in the decision • Trust in recommendations • Propensity to purchase • Perceived cost savings • Perceived cognitive effort	• Amount of information • Degree of control (skip attribute/ cut-off values, specify confidence levels in their specifications, and option of returning back to preference elicitation stages)	• Subjects with high product class knowledge had more positive affective reactions towards agents using WAD and EBA strategies while subjects with low product class knowledge prefer the profile building based agents more. • The two moderators reduced the above interaction effects.
	Widing and Talarzyk (1993)	• Linear weighted-average aid (LINEAR) • Cutoff aid (CUTOFF) • A simple list of alternatives (RANDOM)	• Actual decision quality (switch to alternatives) • Perceived effort • Actual decision time • Perceived decision time	• Correlation between product attributes (negative vs. non-negative)	• In choice sets with negatively correlated attributes, LINEAR leads to superior decisions in comparisons with CUTOFF and RANDOM; CUTOFF takes longer time than LINEAR & RANDOM. • In choice sets with non-negatively correlated attributes, decision quality and decision time were the same across the three aids.

Table 2-1 Prior Agent Studies (cont'd)					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
Interface Design	*Cassell (2000)*	N/A (General Discussion)	N/A	N/A	• Suggestions on the role and implementation of embodied conversational agent interfaces with humanlike features, various conversational functions and modes
	Dehn and Mulken (2000)	N/A (Review paper)	N/A	N/A	• An overview of empirical studies about effects of animated interface agents and the implications and limitations of these studies.
	Lucente (2000)	N/A (General Discussion)	N/A	N/A	• General discussion about conversational interfaces for agents with multi-modes and affable personality
	Höök (2000)	N/A (General Discussion)	N/A	N/A	• Discussion about usability issues for better user-agent interaction design
	Lester and Stone (1997)	N/A (Framework)	N/A	N/A	• Propose a framework for animated pedagogical agents with enhanced believability
	Reilly (1997)	N/A (Framework)	N/A	N/A	• Propose a framework and method to demonstrate an artistic agent personality during user-agent interactions
	Bickmore and Cassell (2001)	N/A (Discussion)	N/A	N/A	• Propose a model of social dialogues aimed at increasing agent trustworthiness
	Bates (1994)	N/A (Discussion)	N/A	N/A	• General discussion about roles of emotion in believable agents
	Carroll (1987)	N/A (Discussion)	N/A	N/A	• General discussion of interface design issues for advice-giving expert systems

Table 2-1 Prior Agent Studies (cont'd)					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
User characteristics, contextual issues, and other factors	*Kaplan et al (2001)*	• Predictive ability information • Locus of control • Involvement	• Decision aid reliance	N/A	• Decision makers are more likely to rely on a decision aid 1) when predictive information is not disclosed, and 2) for decision makers with external locus of control. • Reliance on decision aids for decision makers with internal locus of control is more influenced by involvement than for decision makers with external locus of control.
	King and Hill (1994)	• Conceptual framework for the design of agents based on consumer characteristics (Goal orientation, Autonomy, and Expertise)	N/A	N/A	• Design of different types of agents should incorporate different user characteristics.
	Reneau and Blanthorne (2001)	• Irrelevant distractor information • Information sequence	• Judgment accuracy • Judgment confidence	N/A	• Judgments are more accurate when diagnostic information is presented later and when no irrelevant information is presented. • Judgment confidence is not influenced by these two factors.
	Komiak (2003)	• Familiarity	• Trust (cognitive and emotional) • Intentions to adopt agents as decision aids and to delegate shopping decisions to the agents	N/A	• Familiarity with the agent significant influences cognitive trust, which mediates the effect of familiarity on emotional trust. • Emotional trust influences consumers' intentions to adopt agents as decision aids.

Table 2-1 Prior Agent Studies (cont'd)					
Main Focus	**Study**	**Independent Variable**	**Dependent Variable**	**Moderator**	**Key Finding**
General discussion regarding agent impact, design, and applications	*Maes et al (1999)*	• This paper introduces the applications of various recommendation agents in different stages of consumer decision making.			
	Maes (1994)	• This article discusses the role of agents in reducing work and information overload.			
	O'Keefe and McEachern (1998)	• This paper provides a general discussion about the facilities of online decision support for different stages in consumer decision processes.			
	West et al. (1999)	• This paper examines various roles that agents perform, and discusses the design issues and the goals to be achieved.			
	Grenci and Todd (2002)	• This article discusses the role of customer decision support systems for online consumer decision making.			
	Russo (2002)	• This paper proposes a set of design rules and principles for recommendation agents. Several key considerations such as credibility, trust, and control for the design of recommendation agents are also discussed.			
	Smith (2002)	• This paper discusses the applications of shopbots and their impact on both consumers and retailers.			
	Redmond (2002)	• This article identifies two types of agents and discusses their impact in the short and long run.			
	Iacobucci et al (2000)	• This paper examines the functions of intelligent agents used by service providers on the Internet.			
	Ma and Paul (2003)	• This article examines the functionalities of web-based consumer decision support systems (WCDSS) at different stages of online purchasing process. • The impact of WCDSS on perceived information quality, decision time, consumer satisfaction, and intentions to use is proposed.			
	He and Leung (2002)	• This paper surveys various applications of recommendation agents for business-to-consumer and business-to-business e-commerce.			
	Montgomery et al (2003)	• This article discusses the design issues for shopbots based on a utility model of consumer purchasing behavior. This model considers both the intrinsic value of the product and its attributes, and the disutility aspects as well.			
	Kauffman et al (1999)	• This paper proposes a framework for agent sophistication and several other design concepts for long-lived Internet agents, such as intelligence, validation, concurrency, recovery, monitoring, and interactivity.			
	Milojicic (2002)	• This paper discusses various mobile agent applications.			
	Du, Eldon, and Chang (2003)	• This article provides a framework of mobile agent-based applications.			

Independent Variables	Moderators	Dependent Variables

• Agent availability
• Different types of agents
• Agent-user dialogue design
  −Needs-based
  −Attribute-based
• Preference elicitation
  −Self-expressed
  −Profile rating
  −Reciprocity
  −Sequence
• Explanations
• Agent strategies
• Interface
• Familiarity
• User characteristics
  −Locus of control
  −Involvement
  −Goal orientation
  −Autonomy
  −Expertise
• Other factors
  −Distractor information
	• Information load
	• Degree of control
	  −Skip attributes/
	   cutoff values
	  −Specifying
	   confidence levels
	  −Options to return
	   back
	• Product class
	  knowledge
	• Trust propensity
	• Preference of effort
	  saving vs. decision
	  quality
	• Product types
		• Performance
		  −Decision quality
		  −Consideration set quality
		  −Predictive power
		  −Ability to generate
		   recommendations
		• Cognitive effort
		  −Information search amount
		  −Consideration set size
		  −Time
		  −Perceived effort
		• Trust
		  −Trust in the agent
		  −Trust in the website
		• Satisfaction
		• Attitude
		  −Liking
		• Confidence
		• Tele- and Social-presence of
		  the media
		• Intention/willingness
		  −Agent adoption
		  −Task delegation
		  −Revisit the website
		  −Willingness to pay for
		   service
		  −Personal information/
		   preference revelation
		• Preferences construction
		• Other intervening variables:
		  −Internalization
		  −Transparency

Figure 2-1 Variables Investigated in Prior Agent Studies

As shown in table 2-1, there are four main areas of focus in the prior studies: 1) impact of recommendation agents, 2) comparisons of different types of recommendation agents, 3) impact of particular design features and agent capabilities, and 4) other issues such as user characteristics and conceptual discussion about the impact, design, and

applications of recommendation agents. Figure 2-1 summarizes the main independent variables, moderators, and dependent variables that were examined in the prior empirical studies.

Regarding the effects of recommendation agents, prior studies (e.g., Häubl and Murray, 2003; Häubl and Trifts, 2000) have compared recommendation agents with no recommendation agents and have empirically demonstrated the effects such as increase in consumers' decision quality, reduce in cognitive effort (i.e., amount of information search and consideration set size), and increase in trust in e-vendors.

Two studies have compared different types of recommendation agents. Most recommendation agents in current use fall into two classes (Ansari et al., 2000). The first class is based on a collaborative filtering method (Ansari et al., 2000; Maes et al., 1999). This method does not require consumers to explicitly inform an agent about their needs and preferences, and it uses customer characteristics, mainly based on customer profiles or identified from current and past purchases, to classify customers into groups. Recommendations are then generated based on the products most frequently chosen by others in the same group. This technique best fits situations where inferences of product attributes from consumer needs are difficult, as they are for products based less on utilitarian considerations but more on subjective taste (e.g., books and music), and it may be unsuitable for complex products (Russo, 2002).

The second class, known as content filtering based agents (Ansari et al., 2000), generates recommendations on the basis of agent-user dialogues (Russo, 2002), where consumers answer several questions asked by the recommendation agents regarding their needs and product preferences, and the agents provide shopping recommendations based on their answers.

In addition to these two classes of agents, new methods and algorithms as variants of the above two (e.g., incorporating other statistical methods) have been proposed in many studies. As shown in the review of previous studies, a large amount of recommendation agent types are found in the literature and many studies have been conducted in this area.

This research examines product-brokering recommendation agents that use content filtering techniques. These agents provide shopping advice on what to buy based on user specified needs and preferences. Overall, this type of agents is under-investigated, but they hold great potential for e-commerce because they can provide not only the most-needed advice for a variety of complex products but also more accurate ones (Russo, 2002). Many commercial systems, for example those offered by MyProductAdvisor.com, WiseUncle.com and ActiveDecisions.com, are based on the content-filtering method.

Although many positive effects of recommendation agents have been confirmed in prior studies, many online shoppers still have negative reactions to the recommendation services and they are not willing to disclose their preferences and profiles to obtain recommendations (Burke, 2002). Recommendation agents need to be better designed so that they can deliver their value more effectively and get a higher chance of adoption (Burke, 2002). Accordingly, assessing the impact of various design features for recommendation agents holds great potentials for research. As summarized in table 2-1 and figure 2-1, prior studies about particular agent design issues fall into one of the five aspects: 1) consumer preference elicitation, 2) agent-user dialogue design, 3) agent strategy design, 4) explanation facility design, and 5) interface design.

Several studies have examined issues related to the preference elicitation. Aggarwal and Vaidyanathan (2003) have investigated different ways to elicit users' preferences: conjoint-type full-profile ratings and self-explicated ratings. An agent may infer consumers' preferences for attributes and levels on the basis of their ratings of several alternative products or may directly ask them their evaluations of various attributes and levels. They found that the two methods yield different consumer preferences. Moon (2000) has examined issues about the intimate information [1] elicitation via computers and he has examined the factors (i.e., reciprocity and sequence) that influence consumers' willingness to reveal their preferences and other intimate information. Häubl and Murray (2003) have investigated the impact of elicitation of different product attributes on consumers' preference construction.

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[1] Intimate information is related to disclosers' innermost emotions, attitudes and feelings (Derlega, 1988). Examples of intimate disclosures include, "I am so ashamed of ...," or "I feel so guilty about ...."

Regarding the agent-user dialogue design, Norman (1994) has conceptually discussed issues related to how people interact with computer agents. However, only one study has been found that has empirically examined the design of agent-user dialogues. Komiak (2003) examined needs-based versus attribute-based questions in the agent-user dialogues. Komiak found that need-based questions increased consumers' feelings of agent internalization which enhances their trust in an agent. More research is needed to better design the agent-user dialogues (Norman, 1994). For example, the effectiveness of personalized agent-user dialogues and the impact of user control of the agent-user interactions are promising research areas.

Regarding the agent interface design, many studies have discussed it conceptually. However, few empirical studies were found, hence more research is needed. For example, the impacts of social and anthropomorphic interfaces need to be empirically examined.

Although the above three areas deserve more research, this dissertation focuses on the other two important agent capabilities (i.e., explanation facilities and decision strategy support), which are very important and relevant to IS research and practice. These two aspects are firmly rooted in important IS theories, such as explanation theories for intelligent systems (e.g., Gregor and Benbasat, 1999) and theory of system restrictiveness (e.g., Silver, 1991b). However, no empirical studies have been found to test these theories in the context of web-based recommendation agents. This research aims at bridging these gaps. In sections 2.2 and 2.3, these two aspects are briefly introduced and the choice of them is further justified.

2.2 A Focus on Explanation Facilities

The ability to explain knowledge and reasoning, referred to as explanation facilities, is considered to be one of the critical components of intelligent and knowledge-based systems (KBSs), including decision support systems and online recommendation agents (Dhaliwal and Benbasat, 1996; Gregor and Benbasat, 1999; Hayes-Roth and Jacobstein, 1994; Mao and Benbasat, 2000; Ye and Johnson, 1995). Many prior studies have

examined the impact of explanation facilities on user acceptance of advice from KBS (Ye and Johnson, 1995), and knowledge dissemination (Gregor, 2001; Mao and Benbasat, 1998; Mao and Benbasat, 2001). Extending this line of research, we examine the role and impact of explanation facilities for online recommendation agents.

Recent research on KBS suggests that the role of explanations continues to be fundamentally important (Gregor, 2001). For example, an Internet delivered patient-advocate system requires an explanation facility to adequately meet the needs of patients (Miksch et al., 1997). Sinha and Swearingen (2002) have surveyed 12 participants regarding their understanding of the recommendation generation on their choice confidence and their preferences of several collaborative-filtering based recommender systems. Overall they found users like the systems and feel more confident about recommendations when explanation facilities are provided. In another study, Herlocker et al. (2000) have investigated the impact of explanations provided by collaborative-filtering based agents on the filtering performance and user acceptance of the agents. Twenty-one explanation components were investigated[2]. Seventy-eight participants were surveyed to identify the most compelling components and their effects. They found that explanations improve the acceptance of collaborative filtering based agents.

Nevertheless, so far no guidelines exist for the provision of explanation types particularly for content-filtering based recommendation agents. To our knowledge, this research is the first study that proposes an appropriate set of explanations for them, and advances our knowledge about the impact of explanation facilities for online recommendation agents.

In practice, many online recommendation agents still lack sufficient explanatory capacities. For example, the recommendation agents available from www.activedecisions.com, one of the most well-known recommendation agent providers, do not have explanations regarding why certain questions were asked to elicit consumers preferences and how conclusions were reached. The results of this research will provide

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[2] Indeed, these explanations include all relevant information and description about the agents, the products, and the presentation format of information (e.g., whether or not the movie won awards, histogram or complex graph presented movie ratings). They did not investigate the differential impacts of different types of explanations.

practitioners with design guidelines of explanation facilities for online recommendation agents.

2.3 A Focus on Decision Strategy Support

Online recommendation agents help consumers reduce information overload and improve decision quality (e.g., Haubl and Trifts, 2000; Maes, 1994), but they also restrict consumers to certain decision processes that are supported by the agents (Silver, 1990). Due to the large number of product alternatives available in an online store or across a variety of online stores, the decision strategy supported by an agent must be able to narrow down the product alternatives effectively and retain the products that are most suitable for consumers.

Several studies have investigated the strategies used by recommendation agents. For example, Tan (2003) has examined the impact (i.e., decision accuracy, consideration time, consideration set quality, and consideration size) of different strategies used by screening aids (hyperlink-screen aid, attribute-screen aid, and weight-attribute-screen aid) and sorting aid, and the interaction between these agents and information load. He found that agents with normative strategies (weight-attribute-screen): 1) reduce consumers' cognitive effort, and 2) improve the decision quality when the information load is high.

In another study, Pereira (2000) has explored the interaction between the search strategies (elimination-by-aspect, weighted average method, collaborative-filtering method, and simple hypertext) and subjects' product class knowledge (low, high), in terms of users' satisfaction in the decision process, confidence in the decision, trust in the recommendations, propensity to purchase, perceived cost savings, and perceived cognitive effort. He found that participants with high product class knowledge had more positive affective reactions towards agents using the weighted average and elimination-by-aspect strategies, while subjects with low product class knowledge prefer the collaborative-filtering based agents more.

Nevertheless, the decision strategies utilized by the agents explored in all these studies were pre-configured and each agent employed only one decision strategy. Users had no control over the decision strategies that an agent employed. The concepts of user control and system restrictiveness have been proposed by Silver (1988; 1990; 1991a; 1991b) as an important design concept in the context of decision support systems (DSS). Agent restrictiveness is defined as the extent to which a recommendation agent limits its users' choices and decision-making processes. Since an online recommendation agent includes a finite set of functional capabilities, when a decision-maker relies on an agent to solve a problem, his or her decision-making process is constrained by the agent's capabilities (Silver, 1991b). When a consumer's desired decision strategy is not supported by an agent, the agent will be perceived to be restrictive and the final recommendations may not fit consumers' needs. As a result, the consumer may have negative perceptions about the agent and may not trust it. However, few studies have investigated the impact of agent restrictiveness on consumers' perceptions and evaluations of online recommendation agents.

Working form the theory of system restrictiveness, supplemented by behavioral decision theories (e.g., Payne et al., 1993; Todd and Benbasat, 1992), another focus of this research is to investigate whether or not allowing user control and choice of strategies will influence users' perceptions and evaluations of an agent. Both the benefits and the costs of such design are analyzed.

Our review of current agent applications shows that most of the agents do not allow users to control over the strategy employed by the agents. Due to the high uncertainties involved in online environments (e.g., uncertainty about the quality of an agent's recommendations due to users' inability to touch or feel the products or to communicate with salespersons face-to-face), user control is desirable in that, with appropriate control, users "can be reasonably confident that no major, unpleasant surprises will occur" (Merchant, 1984). As a result, user control can effectively reduce uncertainty perceptions and increase trust (Das and Teng, 1998; Gefen et al., 2003b; Pereira, 2000). Also, the large amount of product alternatives available in Internet shopping environments requires designs for the strategies employed by an agent that can

narrow down the product alternatives and retain the products that are most suitable for consumers. Therefore, the research on the decision strategy support capability has significant practical implications as well.

2.4 Dependent Variables Investigated in the Literature and this Thesis

The major dependent variables, which have been used in prior studies to measure the impacts of recommendation agents and their features and capabilities, mainly falls into five categories as summarized in figure 2-1: 1) agent performance (e.g., decision quality, predictive power), 2) cognitive effort (e.g., consideration set size, perceived effort), 3) user evaluations and perceptions (e.g., attitude, confidence, trust), 4) intentions (e.g., adoption intentions), and 5) others variables including intervening variables (e.g., internalization, transparency).

The core dependent variable explored in this research is consumers' trust in online recommendation agents. Comparing with other variables, trust in online recommendation agents is not well understood and was under-investigated in prior studies. The nature of trust in online recommendation agents is discussed in section 2.5 and defined in section 2.6.

Trust in a recommendation agent significantly influence consumers' intentions to adopt the agent (e.g., Komiak, 2003). Consumers delegate some shopping tasks (e.g., find a product that fits their needs and preferences) to the recommendation agents and the agents work on behalf of the consumers. However, consumers may have some concerns, such as whether or not the agents have the ability to understand consumers' needs and know all potential products that fit their needs, and whether or not the agents are biased toward certain manufacturers. These concerns reduce consumers' trust in the agents and they may perceive relying on such agents to be even detrimental. Consequently, consumers may not be willing to use the recommendation services. In online shopping environments, these concerns are not uncommon due to the lack of proven guarantees that e-vendors or agent providers will not engage in opportunistic behaviors and the lack

of cues to judge the quality of recommendation services (Gefen et al., 2003b). Andersen, Hansen and Andersen (2001) found that trust in recommendation agents is the most important expectation users have. Therefore, the impact of important agent capabilities on users' trust in an agent is examined in this dissertation.

In particular, this research focuses on consumers' initial trust in online recommendation agents that are formed after customers have a first experience with online recommendation agents. While we recognize the importance of the evolving nature of trust, our focus on initial trust is mainly because consumers' perceptions of uncertainty and risk about using recommendation agents are especially salient when they are not familiar with the agents during the initial contact (McKnight et al., 2002b). Therefore, sufficient initial trust in the agents is needed to overcome these perceptions. Otherwise, consumers can easily switch to other websites by a click of the mouse.

Another variable is consumers' intentions to adopt recommendation agents. The value of recommendation services comes from consumers' adoption and use of these services. This research will investigate the effects of the agent features and capabilities mentioned above and examine important intervening variables that influence consumers' adoption decisions.

The mediating variables leading to consumers' trust and intentions to adopt online recommendation agents belong to the other categories of dependent variables mentioned earlier. For the cognitive effort related variables, consideration set size, decision time, and perceived cognitive effort were measured in Experiment 2.

Regarding agent performance, previous studies investigated the decision quality or other similar performance related variables in certain situations. Some of them investigated collaborative-filtering based agents (e.g., Ansari et al., 2000). In these studies, existing data (e.g., a set of product alternatives preferred by each particular user) are available to examine the recommendation quality by checking whether or not the recommendations were actually the products preferred by users.

This research will measure a surrogate variable, participants' competence belief in recommendation agents (one of the trusting beliefs). Competence-belief in an agent means that an individual believes that the agent has the ability, skills, and expertise to perform effectively in specific domains (McKnight et al., 2002a). When consumers make decisions based on an agent's recommendations, their decision quality is influenced by whether or not the agent has the ability and expertise to find suitable products. Therefore, the competence belief in an agent is used as a surrogate variable for the subject measure of decision quality.

Other studies used artificial data for product alternatives including non-dominated alternatives (Haubl and Trifts, 2000). An product alternative is non-dominated if no other alternatives is superior on an attribute without, at the same time, being inferior on at least one other attribute (Haubl and Trifts, 2000). This enables researchers to measure decision quality by checking to what extent the non-dominated alternatives were recommended. In this research, factual product data are preferred because dealing with the trade-offs among product alternatives is actually one of the key tasks that an agent performs (Haubl and Murray, 2003)[3]. It is less necessary to deal with trade-offs if there is non-dominated alternatives because they are better than all other dominated alternatives on all attributes. For factual product data, the best product alternative is difficult to decide because trade-offs are involved in the evaluations of product attributes and it depends on different consumers' needs and preferences.

Another objective way used to measure decision quality is whether or not a shopper, after making a purchase decision, changes his/her mind and switches to another alternatives when he/she is exposed to all product alternatives (Häubl and Trifts, 2000). Given the large amount of product alternatives in online environments, it is also difficult to ask participants to choose one product from hundreds of alternatives. Accordingly, the objective determinant of agent decision quality is difficult. Instead, the perceived competence of an agent is used as a surrogate variable.

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[3] Admittedly, factual data may or may not include non-dominated alternatives.

Finally, this dissertation also identifies other important mediating variables (e.g., perceived cognitive effort, perceived agent transparency, and perceived agent restrictiveness) that influence consumers' trust and intentions to adopt an online recommendation agent. These mediating variables help understand how the agent capabilities influence consumers' evaluations of an agent.

2.5 Trust in Technological Artifacts and Online Recommendation Agents

The importance of trust in online environments has been addressed in many studies (e.g., Gefen et al., 2003b; Jarvenpaa et al., 2000; McKnight and Chervany, 2001; Pavlou, 2003). However, the trust targets in most prior studies are humans, and the nature and role of trust in technological artifacts remain unclear. Trust is a social construction that originates from interpersonal relationships (Sztompka, 1999). The connection between trust and technological artifacts has been the subject of debate in many studies that have explored whether or not technological artifacts can be recipients of trust, and if it is valid to ascribe human characteristics to technological artifacts (Chopra and Wallace, 2003; Corritore et al., 2003).

Some researchers have been opposed to attributing trustworthiness to technological artifacts and have argued that recipients of trust must possess consciousness and agency (Friedman et al., 2000). Humans exhibit these faculties, but "technological artifacts have not yet been produced in substance and structure that warrant in any stringent sense the attribution of consciousness or agency" (Friedman et al., 2000 , p.36). Friedman and Millett (1997) have reported that among the 29 male undergraduate computer science majors they interviewed, 83 percent attributed aspects of agency – either decision-making or intentions – to computers, but only 21 percent consistently held computers *morally responsible* for errors. Thus, the study concluded that users are not totally engaged in social relationships with technology, given that computers are not perceived as completely responsible for the consequences of their use.

Other researchers have agreed that users attribute human characteristics to technological artifacts, but this has been accepted with a measure of caution. Kiesler and Sproull (1997) have argued that any such attribution is an *"as if"* response rather than a true attribution of humanity, i.e., the characterization "may not extend much further than the situation in which the user is tested" (pp. 196-197). Reeves and Nass (1996) have found that *after* participating in controlled experiments, individuals might think that their social behavior toward technological artifacts and the personality they have assigned to the technology are not wholly appropriate. Arguably, computers do not have motivations involving a "self" and dispositions toward social relationships. Nevertheless, it has been demonstrated empirically that people indeed perceive some human properties in technological artifacts *during* their interactions with the technology (Dryer, 1999; Reeves and Nass, 1996).

The other side of the academic debate, favoring the attribution of trustworthiness to technological artifacts, is supported by a large amount of evidence. Conceptually, Sztompka (1999) has argued that trust in a person and trust in a technology are not fundamentally different, because behind all human-made technologies, there stand people who design, operate, and control them. Empirically, Reeves and Nass are among the most prominent researchers who have argued convincingly that people treat computers as social actors and apply social rules to them (Reeves and Nass, 1996). After conducting more than 30 empirical studies on this issue, they have found that even technologically sophisticated people treat technological artifacts (e.g., computers) as if they were human beings, rather than simple tools. People are polite to computers, respond to praise they receive from computers, view them as teammates, and easily assign personalities (e.g., dominance, friendliness and helpfulness) to them. Such social responses apply not only to sophisticated conversational computer agents (Cassell and Bickmore, 2000), but even to computer systems with simple text interfaces (Nass et al., 1997; Reeves and Nass, 1996).

Thus, there is ample and convincing evidence that justifies the treatment of technological artifacts as recipients of social and relational aspects of trust. Furthermore, a variety of studies has extended the attribute of trustworthiness to abstract and technical systems, as well as intelligent computer agents (Komiak and Benbasat, 2004; Muir and

Moray, 1996). For example, Muir and her collaborators (e.g., Muir, 1987; 1996; Muir and Moray, 1996) have included a dimension of *morality* (e.g., responsibility) in their definition of trust in machines and automation. In their experiments, participants were able to evaluate the responsibility of machines in processes of building users' trust. Similarly, in a study of embodied conversational agents by Cassell and Bickmore (2000), trust was defined as a composite of *benevolence* and *credibility*. An agent's benevolence was demonstrated through past examples of benevolent behavior such as third-party affiliations or participation in interaction-based social rituals, such as greetings. Additionally, empirical evidence has indicated that there are no significant differences between the *components* of trust in humans and those in technological artifacts. Notably, Jian, Bisantz and Drury (2000) conducted a word-elicitation study to understand the similarities and differences among human-human trust, trust in human-machine relationships, and trust in general. Their results indicate that particular components of trust are *similar* across these three types of trust (i.e., human-human trust, trust in human-machine relationships, and trust in general). Even in cases of trust in machines, participants use words like "integrity," "honesty," "cruelty," and "harm" to characterize machine behavior.

To summarize, while it may at first appear debatable that technological artifacts can be objects of trust, and that people assign human properties to them, evidence from a variety of relevant literature supports this argument. People respond socially to technological artifacts and perceive that they possess human characteristics (e.g., motivation, integrity, and personality). In particular, research findings have demonstrated that components of trust in humans and in technological artifacts do not differ significantly. This indicates that people not only utilize technological artifacts as tools, but also form social and trusting relationships with them.

2.6 Defining Trust in Online Recommendation Agent

Based on the supporting evidence, we define trust in online recommendation agents as an extension of interpersonal trust that has been extensively studied in the recent literature of

Information Systems (IS) and other disciplines. Recent literature in IS has discussed four general approaches to defining trust (Gefen et al., 2003b; McKnight et al., 2002a): 1) a belief or a collection of beliefs (Bhattacherjee, 2002); 2) emotional feelings (Komiak, 2003); 3) an intention (Mayer et al., 1995); and 4) a combination of these elements (McKnight et al., 2002a). Following the *belief* approach, McKnight et al. (2002a) have defined trusting beliefs as a trustor's perception that the trustee has attributes that are beneficial to the trustor. This *belief* leads to behavioral intentions. In the *emotional feeling* approach, Komiak and Benbasat (2002) have defined trust in terms of feelings of security, comfort, and lack of fear. In the *intention* approach, Mayer et al. (1995) have defined trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party." In the last approach, researchers have treated these elements, such as trusting beliefs and intentions, as components of trust (McKnight et al., 2002a).

This dissertation focuses on trusting beliefs, because trusting beliefs have been identified as important antecedents of trusting intentions and emotional trust (e.g., Komiak, 2003; McKnight et al., 2002a). According to the theory of reasoned action, people's beliefs influence their behavioral intentions (Ajzen and Fishbein, 1980). Also, previous studies have provided empirical evidence that emotions are evoked primarily by cognition (Kahn et al., 2002) and emotional trust in RAs has been studied in prior research (Komiak 2003). Accordingly, this dissertation follows the belief approach to trust.

Adapting the definitions of trust from Komiak (2003) and McKnight et al. (2002a), the current study defines trust in a recommendation agent as an individual's beliefs in an agent's competence, benevolence, and integrity. These three trusting beliefs have been well accepted in many recent studies (McKnight et al., 2002a). According to McKnight et al. (2002a), *competence-belief* means that an individual believes that the agent has the ability, skills, and expertise to perform effectively in specific domains; *benevolence-belief* means that an individual believes that the agent cares about her and acts in her interests; and *integrity-belief* means that an individual believes that the agent

adheres to a set of principles (e.g., honesty and promise keeping) that she finds acceptable. As mentioned earlier, our study concentrates on initial trust. Generally the definition of trust discussed here applies to different temporal contexts including the initial stage of trust formation (Koufaris and Hampton-Sosa, 2004). More detailed discussions of the meaning of trust and general approaches to conceptualizing it can be found in several other studies that have comprehensively reviewed the trust literature (e.g., Gefen et al., 2003b; Mayer et al., 1995; McKnight et al., 2002a).

CHAPTER 3: IMPACT OF EXPLANATIONS ON TRUST IN ONLINE RECOMMENDATION AGENTS

3.1 INTRODUCTION

This chapter empirically investigates how and to what extent the use of explanation facilities increases consumers' trust in online recommendation agents.

Explanation facilities are important components of intelligent systems including recommendation agents. By virtue of making the performance of a system transparent to users, user trust is promoted and user acceptance of an agent is influenced (Gregor and Benbasat, 1999; Hayes-Roth and Jacobstein, 1994). An explanatory capability is thought necessary to imitate behavior that has been demonstrated to be a characteristic of consultations with human experts (Gregor, 2001). Explanation facilities were rated by users as the fourth most important factors among 87 knowledge-based systems (KBS) capabilities (Stylianou et al., 1992). Recent research on KBS shows that the role of explanations continues to be fundamentally important (Gregor, 2001). However, so far no guidelines exist for the provision of explanation types particularly for online recommendation agents and few studies have empirically tested the impact of explanation facilities on consumers' trust in online recommendation agents.

In this light, the research questions investigated in this chapter include: 1) what types of explanations should be embedded in online recommendation agents, and 2) whether or not the use of explanations influences consumers' initial trust in the agents, and if so, how and to what extent. This study identifies the characteristics of online recommendation agents that may hamper consumers' trust-building in the agents. The central premise of this study is that explanations can be used to overcome these constraints, and thus facilitate consumers' trust in the agents. A laboratory experiment was conducted to test the effects of different types of explanations on consumers' trust in recommendation agents.

The remainder of this chapter is organized as follows. Section 3.2 introduces the topic of recommendation agents in e-commerce. Section 3.3 reviews the literature and

theoretical foundations, and develops hypotheses to be tested. Section 3.4 describes the research method and section 3.5 reports the results. This chapter concludes with a discussion of the findings and their implications, as well as the limitations of this research and potential directions for future research.

3.2 RECOMMENDATION AGENTS FOR E-COMMERCE

This study focuses on content filtering recommendation agents that provide consumers with advice about *what to buy* (Ansari et al., 2000). The agents generate recommendations on the basis of agent-user dialogues (Russo, 2002), where consumers answer several questions asked by the recommendation agents regarding their needs and product preferences, and the agents provide shopping recommendations based on their answers. Figure 3-1 is a screen shot of the agent-user dialogue in an experimental platform developed for the current study, and Figure 3-2 gives an example of shopping recommendations arising from the agent-user dialogue. This simulated recommendation agent provides shopping advice for digital cameras.

Figure 3-1 Agent-User Dialogue from the Experimental Agent

Figure 3-2 Recommendations from the Experimental Agent
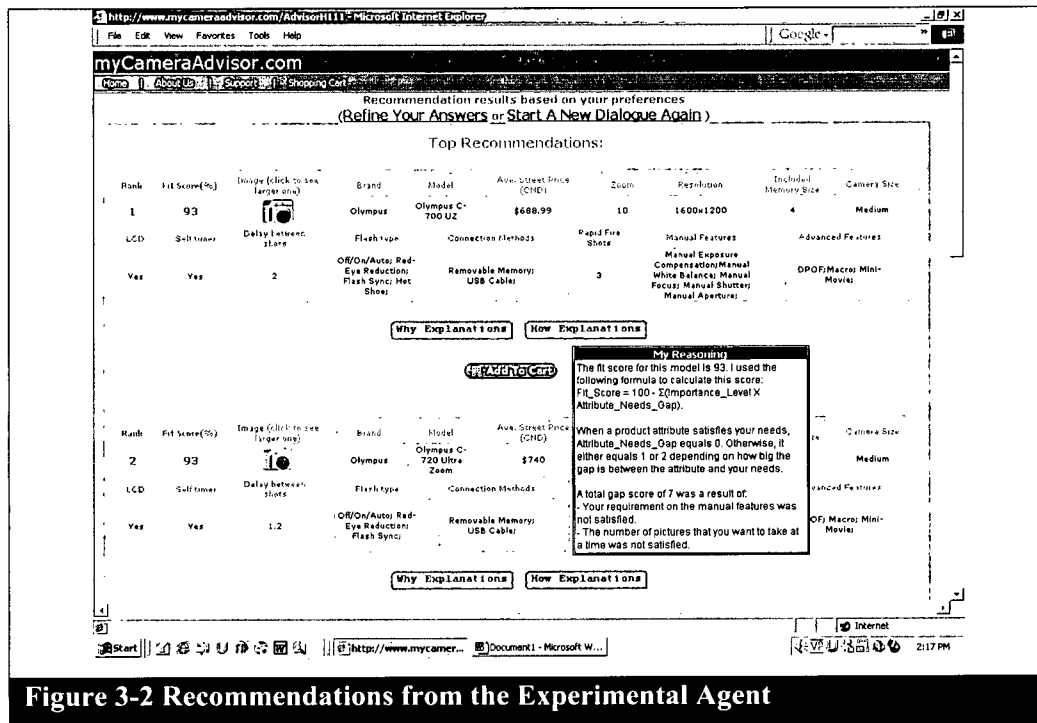
Recommendation agents employed in e-commerce environments are different from traditional KBSs in at least two aspects. First, there is an agency relationship between an agent and its users (principal) because users depend on the agent to find suitable products on their behalf (Bergen and Dutta, 1992). The agency relationship leads to two key concerns – information asymmetry and opportunism. Information asymmetry means that an agent has more information than the principal with respect to the target behavior (i.e., the "procedures" that an agent applies to generate recommendations). Without such knowledge, the principal cannot completely verify the skills and abilities of the agent (Eisenhardt, 1989). Opportunism follows from the fact that the agent can take advantage of users because they lack the oversight of the agent. The agent could be programmed in such a way that focuses on a higher profit for the e-vendors only since the agent is provided and owned by the website and e-vendor. Therefore, there could be goal incongruence between the agent and its users. It is not clear if the agent performs solely for the benefit of its users, or if it provides recommendations that favor its provider who may be a merchant or manufacturer.

Second, users possess a high amount of choice discretion in the agent-user dialogues. When recommendation agents are used to support consumer decision-making, consumers' inputs, composed of their needs, product uses, and preferences, are very flexible. However, lacking adequate knowledge about products, consumers may improperly employ the choice discretion to express their needs. For most products, product attributes are correlated (Widing II and Talarzyk, 1993). For example, a lower price usually means fewer advanced features for a product, and therefore consumers may have to make trade-offs regarding their choices and needs. Without sufficient product knowledge, users may overestimate their real needs and end up with a very powerful product but at a very high price. Consequently, the high amount of discretion may lead to negative user perceptions of the agents.

These two issues hamper consumer trust building in online recommendation agents. The central premise of this study is that appropriate explanations need to be provided to deal with these two issues so that trust-building in recommendation agents will be enhanced.

3.3 HYPOTHESIS DEVELOPMENT

In general, previous research has focused on two areas of study, referred to as *KBS explanations* and *DSS (decision support systems) guidance*. KBS explanations deliver knowledge about a KBS's actions to make it more transparent to its users – what the system does, how it works, and why its actions are appropriate (Gregor and Benbasat, 1999). On the other hand, studies of DSS *guidance* (Barkhi, 2001; Limayem and DeSanctis, 2000; Mahoney et al., 2003; Silver, 1991a; Wilson and Zigurs, 1999) have focused on presenting knowledge that can adequately guide decision makers using the system (e.g., about how to proceed or what input values to use). Based on the explanation literature, three types of explanations (i.e., *how* and *why* explanations from KBS explanations, and *guidance*) will be evaluated as part of online recommendation agents.

Given the three belief components of trust as discussed in section 2.6 (i.e., competence, benevolence, and integrity), we will explore: 1) which types of explanations and knowledge can serve as a direct way to deal with the potential trust obstacles and thus increase consumer trust, and 2) through which trusting beliefs such improvements are realized.

3.3.1 IMPACT OF *HOW* AND *WHY* EXPLANATIONS

Various KBS explanations and different ways to classify them were summarized in the literature (Dhaliwal and Benbasat, 1996; Gregor and Benbasat, 1999). One approach to classify explanations is based on the nature of explanation queries (e.g., *what, why, how, when,* and *where*) (Wick and Slagle, 1989). In particular, the *how* (referred to in some studies as "lines of reasoning") and *why* explanations are of interest in this study because they directly deal with the two main concerns identified with the agency relationships (i.e., information asymmetry and opportunism) and facilitate trust building in recommendation agents.

How explanations reveal the line of reasoning used by agents based on consumer needs and product preferences, and they outline the logical processes involved in reaching final recommendations. *Why* explanations justify the importance and purpose of agents' questions to consumers, in addition to providing justifications for the recommendations provided after the consultation is complete. To elaborate on these explanations, examples are provided in table 3-1. These examples come from the digital camera recommendation agent used in the experiment conducted for this study.

Table 3-1 Examples of *how* explanations, *why* explanations, and *guidance*	
A Question in the Agent-User Dialogue	How far away are the subjects that will be focused on most often by the digital camera? 1). I don't need my camera to focus on anything other than subjects in the immediate vicinity 2). I want a camera that will focus on subjects at a moderate distance 3). I want a camera that will focus on subjects from far away 4). I don't have an opinion on this
How Explanation	Your distance from the subjects you want to focus on will determine the suitable zoom level of a digital camera. If you want a camera that will focus on subjects further away, the camera with stronger optical zoom level will have higher priority in my recommendations. Specifically, the four options will determine the following zoom levels: 1). 2X optical zoom and blow. 2). Between 2X and 5X optical zoom. 3). 4X optical zoom and above. 4). No minimum requirement in zoom capability.
Why Explanation	The purpose of asking this question is to know what kinds of photos you will often take. It is quite useful to take photos at different distances. For example, for portraits of family and friends, subjects are close to a camera, but for many scenery or artistic photos, subjects may be far from your camera.
Guidance	Most digital cameras can take pictures beyond the immediate vicinity. However, cameras capable of taking pictures from very far away will be more expensive. As well, your choices will be more limited (only about 20%). Hence, be careful not to over-estimate your needs.

The *how* and *why* explanations, first introduced in MYCIN (Buchanan and Shortliffe, 1984), remain the foundations of most explanations facilities for current KBS applications (Dhaliwal and Benbasat, 1996). Since users are ultimately responsible for, and are impacted by their choices, they will tend to reject advice from an agent whose reasoning they do not understand (Hollnagel, 1987). Most studies have suggested that explanation facilities can make the advice from a KBS more acceptable to users and more

effective in influencing their beliefs (Ye and Johnson, 1995). Regarding trust, due to the lack of reliable measures that were not available until recently, most studies have used surrogate variables to measure trust (Lerch et al., 1997). A full coverage of the findings of KBS explanation studies is found in Gregor and Benbasat (1999).

In the present study, *how* explanations inform the principal (user) about the "procedures" that an agent applies to generate recommendations. *How* explanations are viewed as links between what buyers know, i.e., their needs, intended uses, preferences and so forth, and what they need to know, i.e., the product attributes that satisfy their needs, uses and preferences (Russo, 2002). With appropriate expertise, the agents are able to generate product recommendations satisfying users' needs and do not miss good product alternatives. However, not explaining agents' behaviors in terms of how they generate the recommendations would create a "knowledge gap" between the agents and their users in that users lack the information regarding the reasoning process of the agent and as a result, they are unable to verify the agent's expertise and ability (Eisenhardt, 1989). *How* explanations alleviate the information asymmetry barrier to trust building by bridging the "knowledge gap."

Furthermore, *how* explanations reveal the underlying reasoning processes that govern the agent's decision making and thus demonstrate the skills, competencies, and expertise that enable agents to generate recommendations. In discussing human trust in an automated system, Lee and Moray (1992) suggest that a system's technical competence is perceived by human operators through their understanding of the underlying processes governing the system's behavior. Muir and Moray (1996) have suggested that trust in machines is based primarily on user perceptions of the expertise of the machine. The skills and expertise that an entity (functioning as a trustee) demonstrates increase its competence in the eyes of its users (the trustors) and hence increase the likelihood that users will trust the entity (Hovland et al., 1953). Therefore,

> *H3-1a: Consumers will have higher* **competence** *beliefs in the recommendation agents with* how *explanations than in those without* how *explanations.*

Benevolence and integrity beliefs are different from the competence belief (McKnight et al., 2002a). *How* explanations demonstrate an agent's skills and expertise in generating product recommendations and deal with the "knowledge gap" between a recommendation agent and its users, which is directly related to the competence belief. Nevertheless, *how* explanations may have some influence on other trusting beliefs as well. For example, by sharing the underlying reasoning processes with consumers, an agent might be perceived to be benevolent. Since there is no direct theoretical or empirical evidence to indicate the extent to which *how* explanations will influence benevolence or integrity beliefs, the impact of how explanations on benevolence and integrity beliefs may not be significant enough. Accordingly, a null effect is predicted and its test is considered as exploratory.

*H3-1b(c): There will be no difference in consumers' **benevolence (integrity)** beliefs in the recommendation agents with and without* how *explanations.*

The provision of *why* explanations is also justified by the existence of agency relationship between recommendation agents and their users. Users of an agent may perceive the existence of agent opportunism due to this agency relationship (Bergen and Dutta, 1992). Users may be concerned that the agent "works" for the provider (the online store or manufacturer), and they may question whether or not the agent puts their interests first. Therefore, not explicitly explaining the good "intention" of the recommendation agents would create an "intention gap." *Why* explanations in this study are used to demonstrate agents' endeavor and purposes of satisfying users' needs, interests, and preferences; they convey the agents' goodwill towards users. Consequently, *why* explanations bridge the potential "intention gap" perceived by users, and thus alleviate their concerns about the agent's opportunism. Given the virtual nature of an Internet-based recommendation agent, there are fewer cues available for consumers to infer an agent's motivation, compared with salespersons in physical stores whose motivations may be discerned from their appearance, attitude, tone, and so forth. Instead, *why* explanations can be used effectively to convey the agent' benevolence in providing recommendation services.

Studies on trust in automated systems suggest that a system's ability to communicate its motivation enhances users' perception of the system's intention (e.g., Muir and Moray, 1996). Motives and intentions are important factors in conveying an impression of benevolence toward others (Cook and Wall, 1980), and by extension, toward to computer systems as well. Trust emerges when a party identifies and understands another party's goals and intentions better (Doney and Cannon, 1997). Therefore:

*H3-2a: Consumers will have higher **benevolence** beliefs in the recommendation agents with why explanations than in those without why explanations.*

Similar to H3-1b and H3-1c, there is no direct theoretical or empirical evidence to indicate the extent to which *why* explanations will influence competence or integrity beliefs. We also hypothesize that:

*H3-2b (c): There will be no difference in consumers' **competence (integrity)** beliefs in the recommendation agents with and without why explanations.*

3.3.2 IMPACT OF *GUIDANCE*

In addition to *how* and *why* explanations, we also suggest the provision of *guidance* in recommendation agents. While interacting with online recommendation agents, consumers have high discretion on what options to select to express their needs in the agent-user dialogues. However, as noted in section 3.2, without sufficient product knowledge and expertise, consumers may be unable to express their needs properly leading to unsuitable product recommendations from the agent (Komiak, 2003). As a result, consumers may have negative perceptions toward the agents. By supplying consumers with relevant knowledge, the provision of *guidance* aims at overcoming this obstacle and facilitating consumer trust in recommendation agents.

Silver (1991a) has defined *guidance* in the context of DSS as knowledge provided in a system to "enlighten or sway its users as they structure and execute their decision-making processes – that is, as they choose among and use the system's functional capabilities" (p. 107). The effects of *guidance* have been empirically tested by several

recent studies. Applying *guidance* to multi-criteria decision-making models, Limayem and DeSanctis (2000) observed that *guidance* enables groups to achieve greater model understanding, increases decision satisfaction, improves perceptions of decision quality, and fosters comfort and respect with the technology. To our knowledge, the impact of *guidance* on user trust building in online recommendation agents is still an unexplored area.

Silver (1990; 1991a) has suggested that the need for and effects of *guidance* depend on a system characteristic, *system restrictiveness*, which refers to the way a system limits its users' choices and decision-making processes. When users have greater discretion in making choices and judgments, as is the case in the task environment used in our study, *guidance* should be of greater value (Silver, 1991a). In the current study, users' discretion lies in their "freedom" to choose different options in the user-agent dialogues. High user discretion works best when users have the relevant knowledge so that they can make choices and judgments wisely and express their needs properly. However, since consumers are not necessarily experts in the product domain they are dealing with, to express their needs properly in the agent-user dialogues, agents need to guide consumers by providing them with relevant knowledge.

Unbiased product information is among the information that online shoppers want most (Nielsen et al., 1999). Marketing research has shown that many people have negative perceptions about salespersons because they are under pressure to achieve their sales quotas and they may provide biased suggestions and guidance (Kopp, 1993). Agent integrity and objectivity are among the main concerns that consumers have when using online recommendation agents and virtual shopping assistants (Komiak et al., 2005). Consumers need objective product information and expertise to make their judgment and choices in the agent-user dialogues. For example, based on their needs, users can choose a corresponding option for each question in an agent-user dialogue, but they also need to know the costs (i.e., price increase or product choice range limitation) of obtaining the product feature that satisfies their needs.

Guidance is not necessarily intended to steer decision makers in a given direction. In some situations it can be suggestive, making judgmental recommendations to users, but in others it may simply be informative, providing users with unbiased, pertinent information (Silver, 1991a). In the context of online recommendation agents, we define *guidance* as the knowledge about potential constraints applied to different choices for each question in the user-agent dialogue, and about how to adjust user needs and preferences accordingly[4]. Table 3-1 presents an example of guidance provided by the experimental agent.

Guidance in this study provides *objective* knowledge regarding the potential constraints brought about by different choices for the questions in the agent-user dialogue. Using *guidance*, consumers will be informed about the potential costs of having different product features (e.g., higher price or limited product choices). Although consumers have the high input choice discretion and can express their needs freely, *guidance* helps consumers make trade-offs and express their needs more properly, influencing the generation of final recommendations. Without such *guidance*, consumers may choose too many desired features or overestimate their needs. Accordingly, the agent might provide products with advanced features and a high price, or provide very few recommendations. As a result, consumers may perceive the agents to be biased. By exposing the constraints of different options, consumers' perceptions of agents' objectivity and honesty will be enhanced through such *guidance*. A trustee is deemed to exhibit high integrity when a trustor believes the trustee has a strong sense of justice, honesty, and objectivity (Mayer et al., 1995). Therefore:

> *H3-3a: Consumers will have higher **integrity** beliefs in the recommendation agents with* guidance *than in those without* guidance.

Similar to H3-1b(c) and H3-2b(c), due to the lack of direct theoretical or empirical evidence to indicate the extent to which *guidance* will influence competence or benevolence beliefs, we hypothesize that:

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[4] Our definition and operationalization of *guidance* does not include knowledge explaining how to use different operators or menus (Silver 1991), because the agent developed is very simple to use.

*H3-3b(c): There will be no difference in consumers' **competence (benevolence)** beliefs in the recommendation agents with and without guidance.*

How explanations, *why* explanations, and *guidance* focus on three independent types of knowledge, namely, agent expertise and line of reasoning in recommendation generation, agent motivation, and objective information for informed inputs. There is no theoretical or empirical evidence to indicate that there will be interactions among *how* explanations, *why* explanations, and *guidance* with respect to different trusting beliefs. Therefore,

H4: There will be no interaction effects among how explanations, why explanations, and guidance with respect to consumers' competence, benevolence or integrity beliefs.

3.3.3 CONTROL VARIABLES

Prior research into explanations and trust suggests a number of additional factors that should be controlled due to their potential influence on trust. Among them are consumers' trust propensity, product expertise, and preferences for effort-saving versus decision quality.

Trust propensity is a personality trait that will affect the likelihood that an entity will exhibit trust (Lee and Turban, 2001; Mayer et al., 1995). As consumers develop trust for trustees, they look for cues and information about the trustees. The trust propensity of individual consumers magnifies, or reduces, the effectiveness of the cues and information provided by trustees (Lee and Turban, 2001). McKnight et al. (2002a) have likewise suggested that consumers' disposition to trust should influence their trusting beliefs. Hence, trust propensity is included in this study as a control variable in analyzing the impact of explanations on trusting beliefs.

Many explanation studies (e.g., Dhaliwal and Benbasat, 1996; Ye and Johnson, 1995) have shown that domain expertise influences the use and effects of explanations. Customers' product expertise provides a foundation for their understanding of the explanations, and therefore, will influence the effects of these explanations.

Consumers' preferences for effort-saving versus decision quality are also included as a control variable because they affect consumers' intentions to use and adopt a computerized decision aid (Todd and Benbasat, 1999). Use and assimilation of the explanations will require cognitive effort, and hence their preference for effort-saving versus decision quality should impact their use and understanding of explanations, and consequently the effects of explanation use.

3.4 RESEARCH METHOD

To examine the effects of the three types of explanations on consumer trust, a 2 × 2 × 2 factorial experimental design was employed. The manipulated factors are *how* explanations (with, without), *why* explanations (with, without), and *guidance* (with, without). All three factors were manipulated between participants.

For the experiment, a recommendation agent for digital cameras that makes recommendations based on the preferences and needs specified by consumers was developed based on a content-filtering method. Our experimental recommendation agent was built to simulate two well-known operational recommendation agents. One is from www.ActiveDecisions.com and the other is from www.dealtime.com. They are the leading agent providers and are widely used by many websites, such as RadioShack.ca and Sony.com. In order to elicit users' preferences and needs, an agent-user dialogue was used to simulate dialogues presented in other studies (Russo, 2002) and in commercial applications. Digital cameras were chosen for two reasons. First, the content-filtering based agent technology works best for relatively complex products (Russo, 2002), and indeed several commercial agents have already been developed for use in the marketing and sale of digital cameras. Digital cameras have a variety of attributes (e.g., zoom and resolution) that require a certain level of expertise from consumers. In addition, an informal survey that we conducted indicated that many undergraduate students do not have digital cameras, although they are interested in them. This ensures a high motivation level for the participants in the experiment.

A user-invoked method was used for explanation provision (Gregor and Benbasat, 1999). In order to reduce users' effort in getting the explanations, pop-up windows were used. When a user pointed the mouse to an explanation icon, an explanation window would appear automatically, and then disappear when the mouse was moved away. A pilot test indicated that most users liked the use of "pop-up" mechanisms to provide explanations.

3.4.1 PILOT TEST ON EXPLANATION VALIDATION

In an effort to assess the face validity and definitional accuracy of the explanations that were incorporated into the agent prototype, a pilot test was conducted. Definitional accuracy refers to how faithfully an explanation represents an operationalization of the definition of its class (Dhaliwal, 1993).

In the pilot test, eight graduate students who are experienced digital camera users were asked to classify the explanations to be examined in this study into one of the three categories (*how* explanation, *why* explanation, and *guidance*) or none of them. 92% of the *how* explanations, 80% of the *why* explanations, and 90% of the *guidance* were correctly classified. The explanations thus appeared to be consistent with their definitions. The suggestions from the pilot test regarding clarity in wording were incorporated into the explanations used for the main experiment.

3.4.2 PARTICIPANTS, INCENTIVES, AND EXPERIMENTAL TASKS AND PROCEDURES

A total of 120 students at a large North American university were recruited for the experiment, with fifteen participants randomly assigned to each of the eight treatment groups. Based on Cohen (1988), the choice of the sample size is to ensure sufficient statistical power (about 80%) at the significance level of .05 when medium effect size (f=.25) was assumed for the main effects as well as the interaction effects of the three types of explanations based on previous empirical studies (Dhaliwal, 1993). To avoid potential biases in their evaluations, only individuals who did not already own digital

cameras were invited to participate in the study[5]. 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 expertise and experience.

The experiment proceeded as follows. A research assistant first trained participants how to use and navigate the assigned Web interface using a tutorial agent that had same features as the experimental agent. 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 was 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 evaluate the agent[6]. Finally, after the two tasks, participants were asked to complete a questionnaire which includes the measures of dependent variables including the trust measures for this chapter and several other constructs analyzed in chapter 4. In the end of the questionnaire, participants were asked to answer several open-ended questions to justify their trust levels in the agents. The written protocols were used to elicit the factors and processes that lead to trust formation and they are analyzed in chapter 5.

Each participant was guaranteed a monetary compensation for his/her participation ($15). 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 participants were told before the experiment that they would be asked to provide their justifications for their choices, and their performance would be judged based on these justifications[7]. The main criterion for the judgment is based on the extent

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[5] The pilot test revealed that participants who already own digital cameras based their evaluations primarily on whether or not the agents recommended the model that they own. Hence, their evaluations might be biased.

[6] 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 completing the questionnaire.

[7] As in many other experimental studies (e.g., Mao and Benbasat 2000), asking participants to provide justifications for their choices is very helpful to make their involvement more serious. However, this may change the goal of the tasks from problem-solving to both problem-solving and learning, which may induce

to which their justifications are appropriate and convincing to support their choice of digital camera.

3.4.3 MEASURES

This study used validated scales for all constructs. The measures for the three trusting beliefs in recommendation agents that were developed and validated by Komiak (2003) have been adapted for the current study. Although Komiak's (2003) trust measure was particularly developed for online recommendation agents, the measure is similar to the web trust measure developed by McKnight et al. (2002a). Measures for the control variables have been adapted from Lee and Turban (2001), Davis (1989), and Komiak (2003). All measurement items are listed in the Appendix of this chapter. Since the constructs were measured by multiple items, summated scales based on the average scores of the multi-items were used in the analysis (1998). Responses were recorded on a nine-point Likert scale[8], with the endpoints labeled as "Extremely disagree" and "Extremely agree."

3.5 DATA ANALYSIS AND FINDINGS

The descriptive statistics are provided in table 3-2. We used Partial Least Squares (PLS), as implemented in PLS Graph version 3.0, to assess the psychometric properties of the trust measures and a detailed measurement validation are reported together with other measures in chapter 4. The measures for the three trusting beliefs have good reliabilities (Cronbach alphas > .70 as indicated in table 3-2) and satisfactory discriminant and convergent validity. We have examined the item loadings, composite reliability of constructs, and average variance extracted (AVE). All of the measures display strongly positive loadings that are significant at the .001 level, indicating high individual item reliability. No item loads higher on another construct than it does on the construct it is

some differences in consumers' use of explanations, and subsequently their evaluations and perceptions of the agent (Gregor and Benbasat 1999). Hence, this could be a limitation of this study.

[8] We used a nine-point scale rather than five- or seven-point scales to cover the relatively vague valuations in consumers' initial trust formation.

designed to measure and the square root of each construct's AVE is greater than the correlations between the construct and others. Therefore, the trust measures have good discriminant and convergent validity.

Table 3-2 Construct Attributes								
Variable	**Mean**	**s.d.**	**Reliability (alpha)**	**1**	**2**	**3**	**4**	**5**
1. Competence	5.55	1.39	.85					
2. Benevolence	6.18	1.29	.77	.65**				
3. Integrity	6.04	1.21	.75	.34**	.51**			
4. Trust Propensity	5.36	.89	.90	.26**	.20*	-.08		
5. Effort vs. Quality[@1]	7.03	1.43	.77	-.06	-.004	.05	-.14	
6. Product Expertise	3.00	1.39	1.00[@2]	.07	.13	-.002	.04	.08

Note: ** p<.01 (2-tailed), *<.05 (2-tailed)

Off-diagonal elements are interconstruct correlations.

[@1] Preference for effort saving versus decision quality

[@2] Product expertise is measured by a single item

A manipulation check was conducted first to examine the extent of participants' use of the explanations. Then, a 2 × 2 × 2 factorial ANCOVA was conducted to test the effects of explanations on consumer trust in recommendation agents, after accounting for the effects of covariates (Hair et al., 1998).

3.5.1 MANIPULATION CHECK

Participants' navigation screens were recorded unobtrusively as videos by screen capture software (Camtasia Recorder 3.0) during the experiments. The author and a research assistant reviewed these videos to count independently participants' use of explanations[9]. Table 3-3 reports the distribution of explanation usage rate in the "with" particular explanation groups. On average, 42% of the *how* explanations, 34% of the *why* explanations, and 47% of the *guidance* were viewed by participants. These usage

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[9] Because Java scripts were used to provide explanations, the client computer and server cannot record participants' use of explanations automatically. The count of explanation use is accomplished objectively. The agreement is close to perfect (98%). We used the average scores of the two judges in the calculations of the explanation use rate.

numbers [10] refer to the average percentage of explanations that were viewed by participants in the different treatment groups. For each type of explanation, all participants who were given explanations viewed at least some of them. Overall, the average usage rates are quite high compared with other empirical studies (e.g., Dhaliwal, 1993). Hence, the three types of explanations in the experimental system are deemed well designed and extensively used[11].

Table 3-3 Frequency Distribution of Explanation Use					
Treatment Group: with *how* explanations		Treatment Group: with *why* explanations		Treatment Group: with *guidance*	
% of *how* explanations used (pc*)	Number of subjects	% of *why* explanations used (pc*)	Number of subjects	% of *guidance* used (pc*)	Number of subjects
pc = 0	0	pc = 0	0	pc = 0	0
0 <pc≤ 10%	8	0 <pc≤ 10%	4	0 <pc≤ 10%	5
10% <pc≤ 30%	9	10% <pc≤ 30%	27	10% <pc≤ 30%	11
30% <pc≤ 50%	16	30% <pc≤ 50%	13	30% <pc≤ 50%	17
50% <pc≤ 70%	23	50% <pc≤ 70%	13	50% <pc≤ 70%	16
pc > 70%	4	pc > 70%	3	pc > 70%	11
Total	60	Total	60	Total	60

Note *: For each type of explanations that are provided to participants in the recommendation agent, the total number of explanations ranged from 26 to 38. Explanations were provided for each question in the agent-user dialogues as well as for each recommendation, if any, after the

[10] The details for the calculation of these percentage numbers are as follows. In the agent-user dialogue, there are 14 questions and after the dialogue, in most cases participants will get 5 recommended products. There will be one *why* explanation for each question and one for each recommended product, in the case of "with *why* explanations" group, for example. Hence, in this group, participants will get 14 *why* explanations, plus 5 *why* explanations if they get 5 recommendations. After the experiment, we counted how many explanations that were viewed by each participant based on the videos. In our example, if a participant viewed 10 *why* explanations for the 14 questions and 3 *why* explanations for the 5 recommended products. Then, for this participant, the usage rate for the *why* explanations is (10+3)/(14+5) = 68.4%. For *how* explanations and *guidance*, the same calculation method is used. The numbers we reported in the chapter is the average number of usage percentages for all participants in the "with" particular explanation conditions.

[11] The extensive usage of explanations also rules out an alternative explanation for the impact of explanations. Because the explanation contents were not automatically provided, they need to be invoked by participants. Accordingly, the impact of explanations should not be simply due to the presence of the explanation icons (i.e., availability). Participants obtained the explanation contents, which generated the impact of explanations.

dialogues. The total number of explanations varied because participants got different numbers of recommendations after the agent-user dialogues.

3.5.2 ANCOVA RESULTS

Of the 120 participants, 62 were female and 58 were male, and 109 were undergraduate and 11 were graduate students. Most participants were in their early 20s. 97% of the participants had more than two years of Internet use experience. No significant differences were found among participants, who were randomly assigned to different treatment groups, with respect to participants' gender, age, Internet experience, online shopping experience, comfort levels with using computers and shopping online.

ANCOVA was conducted to examine the effects of the three types of explanations on the three trusting beliefs. We first examined whether the data satisfy the statistical assumptions of ANCOVA (Hair et al., 1998). Data normality was assessed visually and by the skewness and kurtosis statistics. The skewness and kurtosis statistics indicate that all three dependent variables have normal distributions. Levene statistics indicate no significant differences in different groups. Hence, the assumption of equal error variance of different groups is also satisfied.

Among the three control variables, only trust propensity affected the dependent variable scores significantly at the .05 level. Given that we only invited volunteers who did not have digital cameras to participate in the experiment, the product expertise levels of participants are quite low (average score is 3.0 on a 9-point scale, see table 3-2). Therefore, product expertise levels may not have adequate variances to explain the trust levels. Similarly, the cognitive effort of using the experiment agent is quite low, leading to its inability to explain the trust levels. Hence, in the later analysis, only trust propensity was included as covariates. Group means of trust beliefs are reported in Table 3-4 and ANCOVA results are shown in Tables 3-5 ~ 3-7.

Experimental Condition	N	Competence		Benevolence		Integrity	
		Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
How explanations							
Without	60	5.23	1.45	5.94	1.21	5.89	1.23
With	60	5.86	1.24	6.41	1.33	6.19	1.17
Why explanations							
Without	60	5.46	1.46	5.88	1.38	5.91	1.31
With	60	5.63	1.33	6.47	1.13	6.17	1.08
Guidance							
Without	60	5.48	1.28	6.09	1.21	5.78	1.21
With	60	5.61	1.51	6.26	1.37	6.29	1.15

Table 3-4 Means and Standard Deviations of the Trusting Beliefs for Various Experimental Conditions

Source	DF	Sum of Squares	Mean Square	F	p-value
How explanations	1	12.64	5.15	6.85	**.010**
Why explanations	1	0.02	0.02	.01	.908
Guidance	1	0.47	0.47	.26	.611
Trust Propensity (covariate)	1	15.24	15.24	8.53	**.004**
How * Why	1	3.37	3.37	1.89	.172
How * Guidance	1	0.17	0.17	.09	.759
Why * Guidance	1	0.19	0.19	.10	.747
How * Why * Guidance	1	0.32	0.32	.18	.675
Error	111	198.32	1.79		

Table 3-5 Results of ANCOVA (Dependent Variable: Competence Belief)

Table 3-6 Results of ANCOVA (Dependent Variable: Benevolence Belief)					
Source	DF	Sum of Squares	Mean Square	F	p-value
How explanations	1	6.83	6.83	4.38	**.039**
Why explanations	1	7.69	7.69	4.93	**.028**
Guidance	1	.82	.82	.53	.469
Trust Propensity (covariate)	1	4.71	4.71	3.03	.085
How * Why	1	1.17	1.17	.75	.388
How * Guidance	1	.34	.34	.22	.641
Why * Guidance	1	.06	.06	.04	.847
How * Why * Guidance	1	.04	.04	.02	.879
Error	111	172.96	1.55		

Table 3-7 Results of ANCOVA (Dependent Variable: Integrity Belief)					
Source	DF	Sum of Squares	Mean Square	F	p-value
How explanations	1	2.65	2.65	1.90	.171
Why explanations	1	2.83	2.83	2.03	.158
Guidance	1	7.96	7.96	5.70	**.019**
Trust Propensity (covariate)	1	1.64	1.64	1.18	.280
How * Why	1	2.47	2.47	1.77	.186
How * Guidance	1	.061	.061	.04	.835
Why * Guidance	1	.34	.34	.25	.620
How * Why * Guidance	1	.76	.76	.55	.461
Error	111	155.02	1.39		

All hypotheses except H3-1b are supported. The use of *how* explanations has significant and positive effects on users' competence belief ($F(1,111)=6.85$, $p<0.05$, $f^{12}=0.25$) and benevolence belief ($F(1,111)=4.38$, $p<0.05$, $f=0.19$) in the recommendation agent, but not on integrity belief ($F(1,111)=1.90$, $p>0.1$), at the .05 level. The use of *why* explanations significantly and positively affects users' trust beliefs regarding the agents' benevolence ($F(1,111)=4.93$, $p<0.05$, $f=0.21$) but not on competence ($F(1,110)=0.01$, $p>0.1$) or integrity ($F(1,111)=2.03$, $p>0.1$) beliefs. The use of *guidance* significantly and

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[12] Cohen's (1988) effect size (f) for the ANCOVA was used.

positively affects users' trust beliefs regarding agents' integrity $(F(1,111)=5.70, p<0.05, f=0.23)$ but has no significant effects on competence $(F(1,111)=0.26, p>0.1)$ or benevolence $(F(1,111)=0.53, p>0.1)$ beliefs. As expected, there are no statistically significant two- or three-way interactions among *how* explanations, *why* explanations and *guidance*. Regarding the control variable, trust propensity influences only the competence belief positively and significantly at the .05 level.

We also re-tested the hypotheses by dropping the participants with very low usage of explanations from the sample. ANCOVA was re-performed three times without those participants who used only 1, 2 or fewer, and 3 or fewer explanations, respectively, for any one explanation type (*how, why, guidance*). In all these conditions, none of the conclusions changed, i.e., no effects gained or lost statistical significance at the 5% level, and the changes in the F and p values were slight. Therefore, the results regarding the effects of explanations are quite robust.

Since H3-1b, H3-1c, H3-2b, H3-2c, H3-3b, and H3-3c are hypothesized such that the predictor is not expected to have a main effect on the dependent variables and no significant effects were actually detected, a power analysis was conducted to examine the potential for the type II error (Cohen, 1988). The likelihood of detecting medium effects $(f=.25)$ was about 80 percent for an alpha level of .05 and the likelihood of detecting small effects $(f=.10)$ was under 50 percent.

3.6 DISCUSSION AND IMPLICATIONS

3.6.1 DISCUSSION OF FINDINGS

This experimental study provides strong evidence that explanation provision enhances consumers' initial trust in online recommendation agents. More importantly, this study reveals that different explanation types influence different trusting beliefs: consumers' beliefs in the competence of recommendation agents can be increased by the use of *how* explanations, while their beliefs in the benevolence and integrity of the agents can be increased by the use of *why* explanations and *guidance*, respectively.

Results also show that *how* explanations increase users' benevolence belief in the recommendation agents. Two possible explanations could account for this unpredicted effect. The first is that the questions in the agent-user dialogue are needs-based. Instead of asking users to specify the product attribute levels directly (e.g., the zoom level of a digital camera), the agent inquires about users' preferences for using the product and their needs (e.g. *"How far are the subjects that will be focused on most often by the digital camera?"*). These questions may convey cues that the agent considers users' needs, and such good-will in the agent's motivation may enhance their beliefs in the agent's benevolence (Cook and Wall, 1980). Moreover, when users see the underlying reasoning in the *how* explanations, they may be more confident that the agents care for their needs, as reflected in the nature of the needs-based questions, and as a result, their beliefs about agent benevolence will be further enhanced.

A second possible explanation is that the sharing an agent's underlying reasoning processes with its users may lead users to recognize the agent's benevolence (McKnight et al., 2002b). When an agent is more forthcoming in revealing its reasoning, its behavior will be more predictable in the users' eyes. Consequently, they may be relieved from concerns due to the agency relationship, and their beliefs in the agent's benevolence may be increased.

3.6.2 LIMITATIONS AND FUTURE RESEARCH

Before discussing the implications of this study, we first consider its limitations. Firstly, the application of this study's findings to other types of recommendation agents requires caution. The present study focuses on one type of recommendation agent, namely a content-filtering based product-brokering agent. Explanations that are embedded in other recommendation agents (e.g., collaborative-filtering based agents) might lead to different outcomes, hence additional research is needed.

Secondly, the experimental agent is based on needs-based questions in the agent-user dialogue. However, the agent-user dialogue can be designed in other ways, for example the agent may ask users directly about their preferences for product attributes. In this case, *why* explanations may be more important, because in addition to explaining the

agent's motives, these explanations bridge the gap between attribute levels to be chosen and what users know, i.e., their needs and intended uses. Hence, another potential research topic is to explore the types of explanations needed and their impact when the agent-user dialogues are designed in different ways.

Thirdly, explanations could be implemented differently. Although the validation results demonstrate that the explanations implemented in this study possess satisfactory definitional accuracy, the effectiveness of explanations on enhancing trust might be different when their *contents* change. Additional research is required to test whether or not the results still hold when the contents of explanations are represented differently from the present study. Enhancing the design of explanation contents may have potential to further increase the effectiveness of explanations.

Fourthly, a variety of other explanations provided in traditional KBSs may have the potential to increase trust. The selection of explanations explored in this study was based primarily on the two characteristics of online recommendation agents which introduce some obstacles to trust building. However, other important explanations, e.g., terminological explanations and justifications for reasoning processes (Gregor and Benbasat, 1999), have not been addressed in this study due to cognitive effort considerations. Users may be overloaded if too many explanations are provided (Gregor and Benbasat, 1999). This study controlled for subjects' preferences for effort-saving versus decision quality, which had no effects on trusting beliefs. It is possible that the cognitive cost of using the explanations provided in this study is low thus including additional explanations is feasible. Therefore, other types of explanations that may further enhance consumers' trust in agents deserve attention in future research.

Lastly, since the experimental participants are university students, readers should exercise caution in generalizing the results of this study to other demographic groups. In addition, only one type of product was used. Further research with different participant samples and different types of products is suggested.

3.6.3 IMPLICATIONS FOR RESEARCH AND PRACTICE

Notwithstanding these limitations, this study makes significant contributions to research and practice. The main contribution to IS research is an understanding of customer trust building in online recommendation agents via the use of explanations. The importance of explanations for intelligent systems is well recognized in the IS literature (Dhaliwal and Benbasat, 1996; Gregor and Benbasat, 1999), but empirical testing with validated trust measures has thus far been inadequate. Furthermore, previous studies have produced only generalized suggestions that explanations are influential for user acceptance of KBSs and for improving user trust in the advice provided. This study, in contrast, integrates two streams of explanation use research, KBS explanations and DSS *guidance* studies, and reveals their complementary impact on trust building with explanation facilities: different types of explanations will increase consumer trust via different trust components. The competence belief is increased by the use of *how* explanations; the benevolence belief is increased by the use of *how* and *why* explanation; and the integrity belief is increased by the use of *guidance*. The effects of explanations depend largely on the contents and types of explanations that are provided.

The primary contribution for practice is an effective approach to store knowledge in online recommendation agents to improve consumers' perceptions of agent trustworthiness. In Internet environments, consumers may want to learn from every transaction in order to be more knowledgeable and self-reliant (Saint-Onge, 1998). Explanations in recommendation agents can achieve two goals. First, *why* and *how* explanations facilitate the flow of knowledge from recommendation agents to their users. This knowledge improves users' understanding of and trust in the agents; furthermore, it improves users' knowledge of the particular domains of the agents' expertise, e.g., digital cameras. Second, the flow of knowledge in the form of *guidance* from agents to consumers improves the way that consumers convey their needs and preferences to the agent; as a consequence the recommendations and advice that consumers receive from the agents fit their particular needs and goals much better. These two goals demonstrate that codifying and storing knowledge in recommendation agents and sharing it with customers are very useful when providing shopping advice to consumers. Therefore, with

adequate and appropriate knowledge embedded within them, recommendation agents can be a cost-effective way for companies to provide electronic customer service to facilitate online consumer decision-making.

APPENDIX FOR CHAPTER 3

Trust – Competence

1. This virtual advisor[13] 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.

Perceived Usefulness

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.

Perceived Ease of Use

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.

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[13] We used 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."

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.

Intentions to Adopt Recommendation Agents

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.

Trust Propensity

1. It is easy for me to trust a person/thing[14].

2. My tendency to trust a person/thing is high.

3. I tend to trust a person/thing, even though I have little knowledge of it.

4. Trusting someone or something is difficult for me.

Preference for Effort Saving vs. Decision Quality

1. I am willing to examine the product attributes very carefully in order to make sure that the product fits my preferences perfectly.

2. I prefer to shop hard in order to get exactly what I want.

3. My time is valuable. As soon as I find a product that is adequate for my needs, I will buy it.[15]

Product Expertise

1. I am an expert in digital cameras.

Essay/Self-report Questions for Product Expertise:

1. When, if ever, is "resolution" important for digital cameras?

2. When, if ever, is "zoom" important for digital cameras?

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[14] Clumping "person" and "thing" together might be problematic because there might be some differences between people's reactions to trust in things vs. trust in persons. Therefore, this is also a limitation of this study.

[15] This item was dropped because the reliability was not satisfactory when it was included.

CHAPTER 4: TRUST-TAM FOR ONLINE RECOMMENDATION AGENTS

4.1 INTRODUCTION

This chapter empirically justifies the importance of trust in online recommendation agents by testing an integrated Trust-TAM (Technology Acceptance Model).

As reviewed in chapter 2, the nature of trust in technological artifacts such as online recommendation agents is still an under-studied area: are the dimensions of trust in the agents similar to those of interpersonal trust? If consumers form their trust in the agents, how important is the social and relational aspect of trust in their decision to adopt the agents?

In chapter 2, we reported results about the impact of explanations on consumers' trust in online recommendation agents and confirmed that consumers form a certain level of trust in recommendation agents. This chapter reports the second part of the first experiment about the role of trust in determining consumers' adoption of online recommendation agents. This chapter considers the nature of the technology being studied as well as the online context, and it empirically examines the nomological validity of trust in agents by testing the integrated Trust-TAM model for online recommendation agents. In so doing, this research reveals the relative importance of initial trust vis-à-vis other use antecedents in TAM, i.e. *perceived usefulness* (PU) and *perceived ease of use* (PEOU), in influencing consumers' adoption of online recommendation agents. PU is a measure of an individual's subjective assessment of the utility offered by the recommendation agent while PEOU is an indicator of the cognitive effort needed to learn and to utilize the recommendation agent to make a choice (Davis, 1989; Gefen et al., 2003b). The research results indicate that consumers' initial trust directly influences their decisions to adopt online recommendation agents and also influences consumers' perceptions of usefulness in the agents.

The next section of this chapter develops hypotheses to be tested. The research method has been introduced in the previous chapter. Section 4.3 reports the results. This chapter concludes with a discussion of the results and the implications of the findings.

4.2 HYPOTHESIS DEVELOPMENT

The theory of reasoned action (TRA) (Ajzen and Fishbein, 1980) is generally recognized as the best starting point for studying determinants of individuals' behavior, including their adoption of technology (Sheppard et al., 1988). TAM, which is based on TRA, identifies two key use antecedents (i.e., PU and PEOU) for users' adoption of a technology. The predictive power of PU and PEOU for individuals' technology acceptance has been empirically confirmed by numerous studies (e.g., Lee et al., 2003). A comprehensive discussion is found in Venkatesh et al. (2003).

Previous TAM studies have examined a variety of information technologies (IT) (Venkatesh et al., 2003). In particular, Gentry and Calantone (2002) tested three models explaining behavioral intentions to adopt shopbots (recommendation agents): TRA (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), Theory of Planned Behavior (TPB) (Ajzen, 1985; 1989; 1991), and TAM (Davis, 1989). They found that TAM explains more variance of shopbot adoption than TRA and TPB.

Consumers use recommendation agents to get shopping advice regarding what product to buy as well as where to buy it. The recommendation agents investigated in this study provides shopping advice on what product to buy. According to TAM, more useful and easy to use agents will be employed more readily. Additionally, PU is influenced by the amount of effort users must expend to use the technology (Davis, 1989). An agent that requires less effort and is easier to use will be perceived to be more useful. Therefore,

H4-1: PU of an online recommendation agent will positively affect consumers' intentions to adopt the agent.

H4-2: PEOU of an online recommendation agent will positively affect consumers'
intentions to adopt the agent.

H4-3: PEOU of an online recommendation agent will positively affect PU of the
agent.

Although TAM is considered to be the dominant model for Information Technology (IT) acceptance research (Gefen et al., 2003b; Koufaris, 2002), as pointed out by Davis (1989), more research is needed to address how other variables may influence usefulness, ease of use, and acceptance. In addition to the constructs that are part of the TRA and TPB, other factors that contribute to the explanatory power of TAM could be considered in light of user characteristics, task contexts, and the nature of particular technologies (Moon and Kim, 2001). We identify these factors in the appendix of this chatper, which provides a non-exhaustive summary of studies that have focused on TAM and its extensions.[16]

To account for user characteristics, researchers have examined TAM with the inclusion of constructs such as gender (Gefen et al., 1997; Venkatesh and Morris, 2000), culture (Gefen et al., 1997), training and prior experience with the technology being studied (Davis, 1989; Davis et al., 1989; Gefen et al., 2003a; Igbaria et al., 1995; Taylor and Todd, 1995a; Venkatesh and Morris, 2000; Venkatesh et al., 2003), and Web skills (Koufaris, 2002).

With regard to contexts, issues that have been studied include: 1) voluntary versus mandatory use (e.g., Venkatesh et al., 2003), and 2) offline versus online use for work or shopping (e.g., Gefen et al., 2003b). Recently, a growing number of studies have examined TAM in the context of online shopping. A key question here is whether or not online consumers think and behave differently from their offline counterparts, and researchers have identified several characteristics of online environments that may lead them to do so.

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[16] Due to the large number of articles that have been published using TAM, an exhaustive review of TAM studies is beyond the scope of this study.

First, the impersonal and virtual nature of the Internet involves a physical distance between buyers and sellers, and between buyers and products in online shopping environments (Ba, 2001; Yoon, 2002). The distance between buyers and products is emphasized by the absence of direct methods for online buyers to evaluate products, whereas in physical stores they can understand products better by touching or feeling them. Furthermore, online shopping environments lack human network attributes. Unlike physical shopping environments, where consumers can communicate with salespersons face-to-face, on the Internet fewer audio, visual, and other sensory channels are available for consumers to interact with salespersons and vendors. Consumers are consequently less able to judge product quality and vendor credibility prior to completing purchases, hence facing high uncertainty in their online shopping (e.g., Ba, 2001).

Second, online shopping environments have produced a new spectrum of unregulated activities, but e-vendor behavior is difficult to monitor, and legislation governing online shopping, both in substance and enforcement, is still far from mature (Hamelink, 2001). E-vendors can easily take advantage of online consumers (Gefen et al., 2003b), generating high consumer risk.

Third, online consumers can easily switch among different online vendors, and thus can access more product and vendor choices. This makes consumers more powerful. Consequently, for e-vendors, maintaining high consumer loyalty is difficult in online shopping environments (Koufaris, 2002). Simultaneously, it compels buyers to consider more options, making their decision-making processes more complicated (Maes et al., 1999).

Researchers have considered the nature of online environments, consequently extending TAM with constructs such as *trust* (Gefen et al., 2003a; 2003b), *playfulness* (Moon and Kim, 2001), and *flow* (Koufaris, 2002). Specifically, trust is well-recognized as a key success factor for e-commerce (e.g., Gefen et al., 2003b; McKnight and Chervany, 2001; Ratnasingham, 1998; Urban et al., 2000). Research has shown that trust can effectively address the main issues in relation to the three characteristics discussed above by reducing environmental uncertainty, complexity, and risk, and by enhancing

consumer loyalty (Jarvenpaa and Tractinsky, 1999; Jarvenpaa et al., 2000). If online shoppers do not trust an e-vendor, they will generally stay away from its online store (Jarvenpaa and Tractinsky, 1999; Reichheld and Schefter, 2000).

Arguably, the issues related to the online context also apply to online recommendation agents. Therefore, as asserted by Gefen et al. (2003a; 2003b), in the present study, trust is expected to operate as an antecedent of consumers' intentions to adopt online recommendation agents. TAM has satisfactory explanatory power for various technologies. However, the impact of the nature of particular technology utilized is not yet well understood thus there is a need for extensions of TAM.

Online recommendation agents are perceived to be more than just technologies or tools. They are virtual shopping agents and advisors. Recommendation agents elicit consumer needs and preferences and act on behalf of a principal (consumer) by reflecting her specific needs and preferences. According to Reeves and Nass's Theory of Social Responses to Computers (Reeves and Nass, 1996), consumers treat computerized agents as social actors, and form social relationships that involve trust.

Moreover, web-based recommendation agents are not owned by individual users, and there is an agency relationship between an agent and its users (Bergen and Dutta, 1992). Therefore, trust issues associated with recommendation agents are important and complicated, inasmuch as users may have concerns about the *competence* of an agent to satisfy their needs, as well as concerns about whether an agent is working on their behalf rather than on behalf of a web merchant or manufacturer. Trust can help consumers overcome these concerns, and encourage them to adopt the agents. The benevolence of agents can be engendered by informing users that the agents care about user needs and preferences, and their integrity can be promoted by providing unbiased recommendations and guidance for users.

In sum, although TAM can explain technology acceptance across different technologies, user populations, and contexts, the disparities between online and offline contexts and the special nature of recommendation agent technologies indicate that, in addition to PU and PEOU, trust may also contribute to explaining the user acceptance of

Web-based technologies for online shopping. The integrated Trust-TAM provides a framework to test the nomological validity of trust in technological artifacts. If the construct of trust in online recommendation agents – defined to include three trusting beliefs (competence, benevolence, and integrity) – is valid, it should have predictive power for consumers' adoption of the agents.

Trust has been empirically validated as an important predictor of intended website use by online shoppers (Gefen et al., 2003a; 2003b; Pavlou, 2003). These studies have considered the characteristics of online shopping environments as discussed earlier, and employed trust as a proxy to deal with these characteristics. Consumers' trust in an e-vendor reduces their concerns about the uncertainty, complexity, and risk of online shopping, thus increasing their intentions to use the e-vendor's website (Gefen et al., 2003a; 2003b). Gefen et al. (2003b), conducted a field study targeted at experienced online shoppers, regarding their online book- or CD-shopping experiences. They found that consumer trust in e-vendors is as important to e-commerce adoption intentions as other TAM use antecedents – PU and PEOU. In another study, Gefen et al. (2003a) conducted a free-simulation experiment to compare the relative importance of consumer trust in an e-vendor vis-à-vis TAM use antecedents for new and repeat customers. They found that repeat consumers' purchase intentions were influenced both by their trust in the e-vendor and their perceptions of the website usefulness, while potential consumers were influenced only by their trust in the e-vendor.

Trust is particularly important when consumers interact with recommendation agents for the first time and have a limited understanding of the agents' behavior. During the initial time frame, consumers' perceptions of uncertainty and risk in using the agents are particularly salient (McKnight et al., 2002b). If consumers do not have sufficient initial trust toward a website or an online recommendation agent, they can easily switch to others (Koufaris and Hampton-Sosa, 2004). McKnight, Cummings and Chervany (1998) have found that high initial trust is not only necessary, but also pragmatic and possible. In the context of an organization, high initial trust generally exists among new employees (McKnight et al., 1998). In the online recommendation agent context, Komiak (2003) found that consumers form a certain level of trust in recommendation agents from

their initial interactions with them, and this initial trust significantly influences their intentions to adopt the agents, although their study examined only one antecedent (i.e., trust). Similarly, we hypothesize that:

H6-4: Initial trust in an online recommendation agent will positively affect consumers' intentions to adopt the agent.

It is worthwhile to point out that in prior studies that integrate trust into TAM, the trust objects are e-vendors rather than technologies. To the best of our knowledge, this is the first study to examine the validity of integrated Trust-TAM to explain online recommendation agent adoption with computerized agents as the object of trust. Also, prior studies examined consumers' intentions to purchase through a website, while this study focuses on consumers' intentions to adopt recommendation agents to get shopping advice. Table 4-1 summarizes the key differences between the Trust-TAM models examined in this study and in prior studies.

Table 4-1 Differences between this Study and Previous Trust-TAM Studies		
	This Study	**Prior Trust-TAM Studies** (Gefen et al. 2003a; 2003b; Pavlou 2003)
Trust Targets	Online recommendation agents	e-vendors
PU and PEOU Targets	Online recommendation agents	Websites
Behavioral Intentions	Intentions to adopt agents to get shopping advice	Intentions to use a website and purchase on the website

Trust should also increase the perceived usefulness (PU) of online recommendation agents. Prior research has demonstrated that PU is determined by at least two factors. The first is the PEOU of the agent as predicted in H4-3, and the other is the benefits that users expect to achieve from using agents (Davis, 1989; Gefen et al., 2003b). Users may perceive that agents are untrustworthy for a number of reasons: 1) they may not have appropriate expertise in the task domain, 2) they may function in the interests of web merchants or manufacturers rather than those of consumers, 3) they may lack integrity. Thus, consumers may believe that benefits will not be easily derived from

these agents, and be less likely to adopt them, perhaps even seeing their adoptions as detrimental. The existence of an agency relationship between agents and their consumers determines that such situations are likely to occur. Consumer concerns regarding these issues are not uncommon given the potential harmful opportunistic behavior and higher risks inherent in online environments (Gefen et al., 2003b). As a result, consumers' expectations of gaining benefits from using agents, leading to their perceptions of usefulness, will be influenced their trust in the agents.

H6-5: Initial trust in an online recommendation agent will positively affect PU of the agent.

The integrated Trust-TAM model investigated by Gefen et al. (2003b) also suggests that PEOU increases trust. Gefen et al. have argued that this impact is generated through consumer perceptions that a web merchant is investing in relationships with consumers, and by doing so, the merchant "signals a commitment to the relationship" (p. 65). This argument also applies to online recommendation agents. Ease of use demonstrates that agent providers have expended effort in designing the agents, and that they care about users. Conversely, users may perceive difficult-to-use agents as less capable and less considerate, and thus they may lower their trust in the agents.

H6-6: PEOU in an online recommendation agent will positively affect trust in the agent.

4.3 RESULTS

The method has been introduced in chapter 3. Before the results are reported, the measures used in this chapter are first described.

· We used existing validated scales for all constructs. In addition to trust measures that were explained in chapter 3, measures of PU, PEOU, and intentions to adopt have been adapted from Davis's scale (Davis, 1989). We list all measurement items used in the appendix of chapter 3, and report the construct means and standard deviations in table 4-2.

Table 4-2 Construct Attributes										
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. Intentions to Adopt	7.03	1.29	.93	.89	.48**	.46**	.21*	.54**	.42**	.76

a: Diagonal elements are square roots of the average variance extracted (AVE), and off-diagonal elements are inter-construct correlations.
* indicates that the correlations are significant at the .05 level (2-tailed).
** indicates the correlations are significant at the .01 level (2-tailed).

We used Partial Least Squares (PLS), as implemented in PLS Graph version 3.0, for data analysis. Based on a component-based estimation approach, PLS has been used to assess the psychometric properties of all measures, and subsequently to examine the structural relationships proposed earlier, as illustrated in figure 4-1.
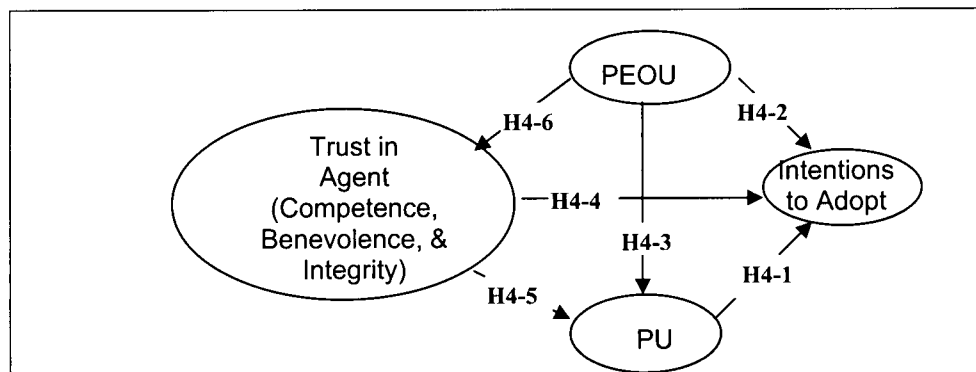
Figure 4-1 Research Model

4.3.1 DATA ANALYSIS FOR THE MEASUREMENT MODEL

Because the three trusting beliefs highly correlate with each other, McKnight et al. (2002a) have suggested that trust be modeled as a reflective second order factor.[17] This

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[17] As argued by Chewelos et al. (2001), "the distinction between formative and reflective constructs is not always clear-cut" (p.312). Given that conceptually the three trusting beliefs should not necessarily covary, we have also tried to model the second order construct of trust as formative and the results showed the

second order construct of trust in online recommendation agents is composed of three sub-constructs (i.e., competence, benevolence, and integrity), which are also measured as reflective. According to previous studies that involve second order factors (e.g., Chwelos et al., 2001), in PLS we have used factor scores of each first order trusting belief as indicators for the second-order constructs of trust in agents.

To assess the reliability (individual item reliability and internal consistency) and validity of the constructs, we have examined the item loadings, composite reliability of constructs, and average variance extracted (AVE). All of the reflective constructs and sub-constructs display strongly positive loadings that are all significant at the .001 level, indicating high individual item reliability. Furthermore, all composite reliabilities and Cronbach's alphas in table 4-2 are greater than .70, which is considered as a benchmark for acceptable reliability (Barclay et al., 1995). The AVE measures the variance captured by the indicators relative to measurement error (Fornell and Larcker, 1981), and it should be greater than .50 to justify using a construct (Barclay et al., 1995). Adequate AVEs for all constructs are indicated in table 4-2.

Barclay et al. (1995) have suggested two criteria to examine discriminant validity. The first criterion requires that the square root of each construct's AVE is greater than the correlations between the construct and others, thereby indicating that the construct shares more variance with its own measures than it shares with other constructs. This criterion is satisfied by the current data, as demonstrated in table 4-2. The second criterion requires that no item loads higher on another construct than it does on the construct it is designed to measure. The factor- and cross-loadings reported in table 4-3 demonstrate adequate discriminant validity except one item PEOU4. It loads equally highly on PEOU and on PU and hence has been dropped in later analysis.

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same patterns: no paths gained or lost statistical significance, no significant paths changed in sign, and the changes in the path values were very slight. Therefore, the results of this study should not be an artifact of our modeling decisions.

Table 4-3 Factor Loadings and Cross-Loadings					
Items	Competence (CMPT)	Benevolence (BNVL)	Integrity (INTG)	Perceived Usefulness (PU)	Perceived Ease of Use (PEOU)	Intentions 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**	.63	.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**

4.3.2 DATA ANALYSIS FOR THE STRUCTURAL MODEL

The results of the structural model from PLS, including path coefficients, explained variances, and significant levels, are illustrated in figure 4-2. We report the total effects of the three antecedents as well as the direct and indirect effects in table 4-4.

** indicates a significance level of .01;
* indicates a significance level of .05;
n.s. indicates a non-significant path.

Figure 4-2 PLS Results
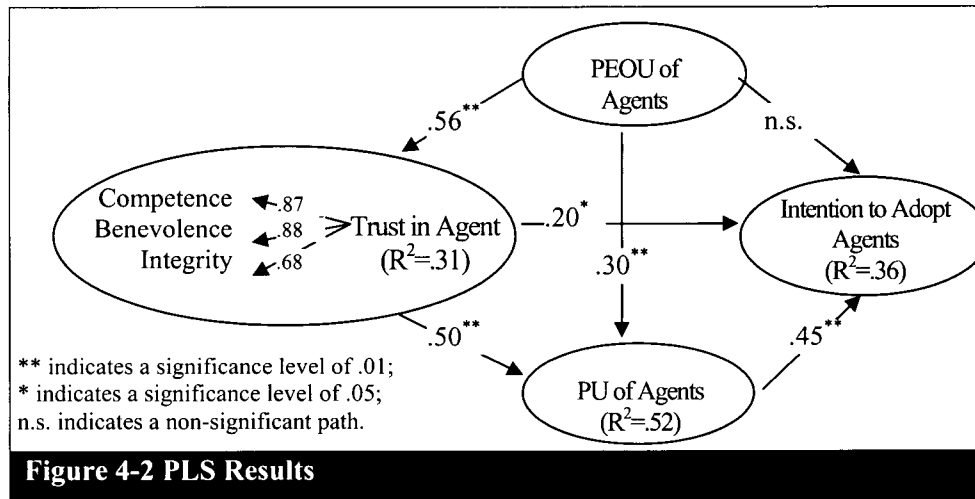
Table 4-4 Structural Model Results

Hypothesis	Standardized Path Coefficient (direct effect)	t-value for Path	Indirect Effect	Total Effect[a]
H₁: PU → Adoption Intentions	.45	3.97	--	**.45**
H₂: PEOU → Adoption Intentions	--	--	.25	**.25**
H₃: PEOU → PU	.30	3.64	.28	.58
H₄: Trust → Adoption Intentions	.20	2.13	.23	**.43**
H₅: Trust → PU	.50	8.04	--	.50
H₆: PEOU → Trust	.56	7.76	--	.56

Our analysis indicates that all of the hypotheses except for H4-2 are supported by data from the experiment. Consumers' initial trust and PU have significant impact on their intentions to adopt recommendation agents, while PEOU does not. Therefore, H4-1 and H4-4 are supported, while H4-2 is not. Consumers' initial trust and PEOU influence their PU of the agents significantly, supporting H4-5 and H4-3. PEOU also influence consumers' trust in agents significantly, supporting H4-6. The significant results regarding the impact of trust on PU and on intentions, as well as the impact of PEOU on trust, confirm the nomological validity of trust in online recommendation agents.

Consumers' initial trust directly influences their intentions to adopt the recommendation agents, while also exhibiting indirect effects through the consumers' increased PU of the agents. The experiment results listed in table 4-4 indicate that PU exerts the most determinative influence over intentions to adopt, in terms of direct effects. The total effects of PU and trust on intentions are similar and stronger than those of PEOU. The impact of PEOU on intentions to adopt agents is fully mediated by PU and trust. This finding is not uncommon, however, inasmuch as many other TAM studies (e.g., Davis, 1989) have found that PEOU is mediated by PU, and Gefen et al. (2003a) have also found that PEOU is mediated by trust, though this was tested only with experienced consumers.

The variance in adoption intentions explained by trust, PU, and PEOU in this study is 36 percent, which is relatively high compared to the results of Gefen et al. (2003a), who found that 27 percent of the variance in purchase intentions was explained by trust and PU. This confirms the validity of the integrated Trust-TAM to explain online recommendation agent adoption.

Furthermore, the relative importance of the three trusting beliefs in predicting adoption intentions is also revealed by the loadings of the three trusting beliefs on the second order trust, which are all significant at the level of .001. Consumers' initial beliefs in the competence (.87) and benevolence (.88) of online recommendation agents have similar but higher importance than their beliefs in the integrity (.68) of the agents, during their deliberations about adopting the agents.

4.4 DISCUSSION

4.4.1 SUMMARY AND DISCUSSION OF RESULTS

The study has explored the nature of trust in online recommendation agents. Based on the theoretical and empirical work described in the literature, we extended interpersonal trust to trust in online recommendation agents. Data from this study confirm the nomological validity of trust in recommendation agents and the validity of Trust-TAM for online

recommendation agents. The significant loadings of the three trusting beliefs (competence, benevolence, and integrity) indicate that all of them hold for trust in online recommendation agents. When interacting with online recommendation agents, consumers appear to treat computer agents as "social actors" and perceive human characteristics (e.g., benevolence and integrity) in the agents. Regarding the integrated Trust-TAM, this study reaches similar results as other trust and TAM studies, even though the trust objects in this study are technological artifacts.

The analysis shows that consumers' initial trust in agents affected PU of agents and their intentions to adopt the agents. However, unlike Gefen et al. (2003a) who found that potential customers' purchase intentions were only influenced by their trust in e-vendors, we found that for new consumers, both trust in agents and PU of the agents have direct effects on adoption intentions. Consumers perceive online recommendation agents not only as support tools for online shopping, but also as "social actors" (virtual advisors) with human characteristics. Both the usefulness of the agents as *tools* that provide recommendations and consumers' trust in the agents as *virtual assistants* are influential in consumers' intentions to adopt the agents.

One factor that may explain the above discrepancy is the different behavioral intentions explored in different studies as summarized in table 4-1. This study focuses on consumers' intentions to use agents to get recommendations. Consumers did not delegate the whole purchase task to agents and they did not have to act upon the product recommendations provided. Therefore, relatively low risks were involved. Conversely, Gefen et al. (2003a) explored consumers' purchase intentions. Purchase behaviors involve high uncertainties and risks (e.g., financial loss, personal information and privacy concerns). In such situations, trust might be more salient and it may constitute a powerful determinant of purchase intentions for potential consumers.

4.4.2 LIMITATIONS

The major limitations of the first experiment have been reported in chapter 3. In addition, this chapter has another limitation. Some issues should be addressed regarding the analytic methodology used in the current study. The potential for common method

variance may exist because measurements of all of the constructs in this study were collected at the same point in time and via the same instrument (Straub et al., 1995). To test common method bias, we applied Harmon's *one-factor test* to data from the current experiment (Podsakoff and Organ, 1986). We performed an exploratory factor analysis on all the variables, but no single factor was observed and no single factor accounted for a majority of the covariance in the variables, suggesting that common method bias is not a concern in the present study.

4.4.3 IMPLICATIONS AND FUTURE RESEARCH

Due to advances in Web-based technologies, there are ample opportunities to utilize knowledge-based systems to facilitate online consumer decision making and provide recommendation services for consumers. However, because of the high risks and uncertainties inherent in online environments, consumers must trust in Web-based technologies in order for them to be effective. Interpersonal trust has been the focus of many previous studies, and trust in technological artifacts remains an under-researched area. The present study has implications for information systems research on the role of trust in users' acceptance of online recommendation agents.

Results from this study and prior literature show that the nature of trust in technological artifacts should not be fundamentally different from interpersonal trust. Therefore, trust theories in the interpersonal domain may generally apply to trust in technological artifacts. Nevertheless, there might be unique elements for trust in technological artifacts. More research is needed to examine whether the conceptualization of trust in technological artifacts should be extended to include other relevant beliefs. For example, Lerch et al. (1993) and Muir (1994) have explored other machine trust related beliefs such as reliability, predictability, dependability, and faith as they relate to machines. In addition, to further extend the line of research on the relational aspect of trust in agents, researchers may need to identify emotional elements in consumer trust in online recommendation agents (Komiak and Benbasat, 2004; Rempel et al., 1985).

The issue of different targets of trust also deserves further research. The relative importance of different trust dimensions might be different for different trust targets. Although the effect of trust in recommendation agents on the intentions to adopt agents has been confirmed in this study, the role of agents in consumers' trust in e-vendors and the reciprocal impacts of agent and vendor trust have not been studied. Urban et al. (2000) suggest that recommendation agent technology is an effective way of promoting consumer trust in e-vendors. Trust in e-vendors can also be extended to online recommendation agents via the transference process (Doney and Cannon, 1997). Especially, for initial trust building, consumers rely on other relevant sources (e.g., the e-vendors and their websites) to judge the trustworthiness of recommendation agents. Additional empirical research is needed to investigate such mutual influences.

As shown in table 4-1, in contrast to Gefen et al. (2003a; 2003b) and Pavlou (2003), this study focuses on trust in and adoption of online recommendation agents. These previous studies tested similar models in which e-vendors were the trust targets, and PU and PEOU were measured in relation to websites. However, the influence of consumers' perceptions and use of recommendation agents available on websites of a company on their perceptions and use of the websites themselves is still an open research question. In addition to the reciprocal impacts of agent and vendor trust, it is possible that PU, PEOU, and adoptions of the agents will influence consumers' PU, PEOU, and use of the websites. Furthermore, it is not clear whether trust in agents will influence consumers' purchase behavior directly or only indirectly through consumers' trust in the e-vendor and PU of the website. The relationships between the two adoption models (i.e., adoption of agents and websites) require future research.

This study also suggests a new perspective for studying IT acceptance research and provides an initial blueprint to investigate relationship building with technologies. In TAM (Davis, 1989), the dominant IT adoption model, IT acceptance is determined by rational processes focusing on expected outcomes such as usefulness. As summarized by Gefen and Straub (2003), "in that line of research, social aspects were secondary, if mentioned at all; social aspects were studied in the context of how they influenced perceived usefulness and ease of use" (p.21). Recently, several studies (e.g., Gefen et al.,

2003a; Gefen et al., 2003b; Gefen and Straub, 2003; Pavlou, 2003) have looked into the role of social factors (e.g., trust) as direct antecedents of behavioral intentions. However, the social factors in most of these studies were examined in the context of interpersonal relationships between consumers and e-vendors. The "social" relationships between consumers and technologies, such as agents, were largely ignored. This study, on the other hand, confirms the importance of such perceptions and highlights the role of relational factors in consumers' intentions to adopt online technologies.

Furthermore, the findings of this research can be extended to other decision support systems or knowledge-based systems as well. The integrated Trust-TAM may provide a more complete model to explain the user acceptance of these systems. When consumers utilize decision support systems or knowledge-based systems, they face a set of risks and uncertainties (e.g., whether or not a system is reliable and has the competence to improve task performance). Therefore, trust in the system is a factor of system acceptance.

This study also has important practical implications for the design of effective online recommendation agents. Particularly, relational and social relationships between consumers and online recommendation agents are important, as positive relationships induce consumer trust in agents and promote agent adoption. A strong, personal connection to customers via web technologies should be one of the key goals of web vendors. Designers could employ several social relationship building mechanisms to induce consumer trust in the agents (Komiak et al., 2005). For example, designers may consider creating personalized agents that know individual users' backgrounds and greet them when they initiate agent applications. Anthropomorphic features (e.g., a human-like body with gestures and emotional reactions) can also be designed into the agents (Qiu, 2002).

There are other important agent capabilities that enhance the trustworthiness of online recommendation agents. As key trust building mechanisms, the appropriate explanation facilities studied in chapter 3 should be embedded in online recommendation agents. In addition, Xiao and Benbasat (2002) have investigated the internalization

capabilities of recommendation agents. *Agent internalization* refers to an agent's ability to understand users' real needs, and its ability to apply those needs when generating recommendations (Xiao and Benbasat, 2002). A clear example of high internalization is an agent that effectively elicits consumers' desires by asking appropriate needs-based questions. Their results indicate that consumers invest greater trust in recommendation agents with higher internalization capabilities. By incorporating these important trust-inducing features, recommendation agents can provide more effective services, gain a higher chance of user acceptance, and further promote consumer intentions to transact with the web vendors.

APPENDIX FOR CHAPTER 4

Table A4-1 Pervious TAM Extension Studies					
Studies	**Constructs[a]**	**Technologies**	**Users Characteristics**	**Context**	**Findings**
Davis (1989)	PU, PEOU, Usage/BI	PROFS email; XEDIT file editor; Chart-Master & Pendraw graphic systems.	Not investigated, experienced users for one study and new users for the other	Offline, voluntary use for work	PU $\rightarrow$ Usage/BI; PEOU $\rightarrow$ PU
Davis et al. (1989)	PU, PEOU, A, BI, Usage	WriteOne word processing	Experience (through a longitudinal study: both initial and one semester later)	Offline, voluntary use for work	PU $\rightarrow$ A; PEOU $\rightarrow$ A[1]; PEOU $\rightarrow$ PU; A $\rightarrow$ BI[1]; PEOU $\rightarrow$ BI[1]; PU $\rightarrow$ BI; BI $\rightarrow$ Usage
Mathieson (1991)	PU, PEOU, A, BI	Spreadsheet, calculator	Not investigated	Offline, voluntary use for work	PU $\rightarrow$ A; PEOU $\rightarrow$ A; PEOU $\rightarrow$ PU; PU $\rightarrow$ BI; A $\rightarrow$ BI
Adams et al. (1992)	PU, PEOU, Usage	Voice mail and email, WordPerfect, Lotus 1-2-3, Harvard Graphics	Not investigated	Offline, voluntary use for work	PU $\rightarrow$ Usage[5]; PEOU $\rightarrow$ Usage[6]; PEOU $\rightarrow$ PU;
Igbaria et al. (1995)	EV, PEOU, PU, Usage	Micro-computer	User training, computer experience	Offline, voluntary use for work	EV $\rightarrow$ PEOU; EV $\rightarrow$ PU; PEOU $\rightarrow$ PU; PU $\rightarrow$ Usage;

Table A4-1 Pervious TAM Extension Studies (Continued)					
Studies	**Constructs**[a]	**Technologies**	**Users Characteristics**	**Context**	**Findings**
Chau (1996)	PEOU, near-term PU, long-term PU, BI	Word, Excel	Not investigated	Offline, voluntary use for work	PEOU → Near-term PU; PEOU → BI; Near-term PU → Long-term PU; Near-term PU → BI; Long-term PU → BI
Gefen et al. (1997)	PU, PEOU, SPIR, Gender, Usage	Email	Gender, culture	Offline, voluntary use for work	Gender → PU; Gender → PEOU; Gender → SPIR; SPIR → PU; PU → Usage
Taylor and Todd (1995a)	PU, PEOU, A, SN, PBC, BI, Usage	Computer resource center	Prior experience	Offline, voluntary use for work and study	PEOU → PU; PU → A; PEOU → A[1]; PU → BI; SN → BI; PBC → BI; BI → Usage; PBC → Usage[1]
Taylor and Todd (1995b)	PU, PEOU, A, BI, Usage	Computer resource center	Not investigated, most participants were familiar with the technologies	Offline, voluntary use for work and study	PEOU → PU; PU → A; PEOU → A; PU → BI; BI → Usage
Venkatesh and Morris (2000)	PU, PEOU, SN, BI, Gender, Experience	Various systems for data and information retrieval	Gender; experience (through longitudinal study: post training, after one month, and after three months)	Offline, voluntary use for work	PU → BI; PEOU → BI; PEOU → PU; SN → BI[2]

Table A4-1 Pervious TAM Extension Studies (Continued)					
Studies	**Constructs[a]**	**Technologies**	**Users Characteristics**	**Context**	**Findings**
Venkatesh et al. (2003)	PU, PEOU, SN, BI	*Sophisticated* organizational technologies (e.g., Portfolio Analyzer)	experience (through longitudinal study: post training, after one month, and after three months)	Offline, voluntary and mandatory use	PU → BI; PEOU → BI[3]; SN → BI[4]
Gefen et al. (2003a)	PU, PEOU, BI, Trust, Familiarity	WWW Website	Experience with online stores	Online, voluntary use for shopping	PEOU → PU; PU → BI[1]; Trust → BI; Familiarity → BI; Familiarity → PEOU; Familiarity → Trust
Gefen et al. (2003b)	PU, PEOU, BI, Trust	WWW Website	Not investigated (experienced shoppers only)	Online, voluntary use for shopping	PEOU → PU; PEOU → Trust; PEOU → BI; PU → BI; Trust → PU; Trust → BI;
Koufaris (2002)	PU, PEOU, BI, Flow (PC, Enjoyment, Concentration)	WWW Website	Web Skills	Online, voluntary use for shopping	PU → BI; Enjoyment → BI
Lederer et al. (2000)	PU, PEOU, Usage	WWW (Work-related Internet newsgroups)	Not investigated (mostly experienced Internet users)	Online, voluntary use for work	PU → Usage; PEOU → Usage

Table A4-1 Pervious TAM Extension Studies (Continued)					
Studies	**Constructs[a]**	**Technologies**	**Users Characteristics**	**Context**	**Findings**
Moon and Kim (2001)	PU, PEOU, Playfulness, A, BI, Usage	WWW websites	Not investigated	Online, voluntary use	PU → A; PEOU → A; Playfulness → A; Playfulness → PEOU; PEOU → PU; PU → BI; Playfulness → BI; A → BI; BI → Usage
Gentry and Calantone (2002)	PU, PEOU, A, BI	Shopping Bots on WWW	Not investigated	Online, voluntary use for shopping	PEOU → PU; PU → A; PU → BI;

[a] Legend: A – attitude; BI – behavioral intentions; SN – subjective norm; PBC – perceived behavioral control; PC – perceived control; SPIR – social presence and information richness; EV – external variables (e.g., individual, system, and organizational characteristics)

[1] The relationship is significant only when participants use the software/technology/computer center/Website for the first time.

[2] This relationship is significant only for the post training and after one month tests but not for the after three months test.

[3] In the voluntary settings, this relationship is significant only for the post-training test; in the mandatory settings, this relationship is significant for the post-training and after one-month tests.

[4] This relationship is significant only for the post-training test in the mandatory settings.

[5] This relationship is significant except for the WordPerfect case and the Harvard Graphics case.

[6] This relationship is significant except for the Email case and the Voice mail case.

CHAPTER 5: ANALYSIS OF TRUST FORMATION PROCESSES IN ONLINE RECOMMENDATION AGENTS

5.1 INTRODUCTION

This chapter identifies the key processes through which consumers' trust in online recommendation agents is enhanced or inhibited.

Given the high risks and uncertainties involved in the use of agent technologies in online environments as discussed in chapter 4, building trustworthy online recommendation agents is a challenging task. There is little empirical research on the antecedents and formation of trust in the context of online recommendation agents. This study investigates the processes that build and inhibit[18] trust in recommendation agents. Fragility is one of the important qualities of trust (Ba and Pavlou, 2002; Blomqvist, 1997; Gallivan, 2001; Jarvenpaa and Leidner, 1998; Kramer, 1999; Lewicki and Bunker, 1995; McKnight et al., 1998; Meyerson et al., 1996; Ring, 1996; Ruppel et al., 2002-2003; Shankar et al., 2002; Shneiderman, 2000; Slovic, 1993; Worchel, 1979). Researchers have noticed the asymmetry between the trust-building processes and trust-inhibiting processes in the domain of interpersonal perceptions (e.g., Slovic, 1993). Many researchers have argued that trust is easier to destroy than to create (e.g., Shneiderman, 2000; Slovic, 1993). Especially during the initial stage of trust formation when there is no previous interaction history to rely on, trust is fragile and may be easily destroyed because consumers' perceptions are inherently fluid (Lewicki and Bunker, 1995; Papadopoulou et al., 2001; Ring, 1996). Recent IS research calls for attention for unique factors and processes that contribute to technology usage inhibitors (Cenfetelli, 2004), but there are few empirical studies that focus on the processes leading to the deterioration and decline of trust in recommendation agents.

To open the "black box" of consumers' trust-building and trust-inhibiting processes, we analyzed the written protocols that participants used to justify their trust

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[18] The inhibiting processes that lead to trust deterioration and decline is different from the concept of distrust (e.g., Lewicki and Bunker, 1995; Kramer, 1999). The issue of distrust is also important but beyond the scope of this study.

levels after interacting with a recommendation agent in Experiment 1. Using a prior-research-driven approach (Boyatzis, 1998) and mainly based on Komiak (2003) and Komiak and Benbasat (2003)'s classification scheme, a new agent trust formation scheme was developed to code the written-protocols. As reported in chapters 3 and 4, participants' trust perceptions were surveyed in Experiment 1. The major trust-building and trust-inhibiting processes resulting from the protocol analysis were then used to predict participants' trust levels in a Partial Least Squares (PLS) analysis. Using both an interpretive approach and a quantitative analysis provides us more confidence in revealing the most influential trust formation processes. Based on these trust formation processes, guidelines for the design of trustworthy online recommendation agents are discussed.

The chapter proceeds as follows. Section 5.2 reviews the process theories of initial trust formation. Section 5.3 describes the research method. Section 5.4 presents the data analysis and describes the coding scheme. The results are reported in section 5.5, and this chapter ends with a discussion of the results, and limitations and implications of this chapter.

5.2 PROCESS THEORIES OF INITIAL TRUST FORMATION

Drawing from research in various disciplines (e.g., psychology, sociology, political sciences, economics, marketing, and organizational sciences), process theories of initial trust formation shed light on how initial trust forms in interpersonal and organizational contexts (Brashear et al., 2003; Doney and Cannon, 1997; Gefen, 2004; Gefen et al., 2003b; Komiak, 2003; Komiak and Benbasat, 2003; Lewicki and Bunker, 1995; McKnight et al., 1998; Zucker, 1986). To analyze consumers' trust formation processes in online recommendation agents, we followed Boyatzis (1998)'s prior-research- and theory-driven approach to develop a coding scheme. This study used Komiak (2003, see also Komiak and Benbasat, 2003)'s scheme of trust formation in recommendation agents as a basis for the development of a coding scheme, but it also covered other major processes discussed in other studies.

Based on McKnight et al. (1998), Doney and Cannon (1997), Zucker (1986), Lewicki and Bunker (1995), and Komiak (2003), table 5-1 categorizes the major trust building processes into six clusters: (1) personality based, (2) institution based, (3) calculative based, (4) heuristic based, (5) process based, and (6) knowledge based.

Table 5-1 A Summary of Trust Building Mechanisms						
Study ⟍ Process	McKnight et al. (1998) – initial trust among employee in an organization	Doney & Cannon (1997) – buyer trust in a supplier firm and its salesperson	Zucker 1986 – General trust	Lewicki and Bunker (1995) – General trust	Komiak (2003) – consumer trust in recommendation agents	This study – consumer trust in recommendation agents
1.Personality based						
Dispositional Process	√ (Trusting stance & Faith in humanity)					√
2.Institution based						
Situational normality	√					
Structural assurance	√		√ (formal societal structures & intermediary mechanisms)			√
Risk awareness						
3. Calculative based						
Calculative Process	√	√		√ (calculus process)		√
4. Heuristic based						
Categorization Processes	√		√ (characteristic based process)			
Illusions of Control Process	√					
Transference Process		√				√
Media Assessment					√	√

Table 5-1 A Summary of Trust Building Mechanisms (cont'd)

5. Process based						
Expectation Confirmation					√	√
Verification Process			√ (process based process)		√	√
Utility Assessment						√
Control Process					√	√
6. Knowledge based						
Information Sharing Process	Knowledge based Process			Knowledge based Process	√	√
Prediction Process		√				√
"Unknown" Awareness Process					√	√
Competence Assessment		√ (capacity process)			√	
Benevolence Assessment		√ (intentionality assessment)			√	
Integrity Assessment					√	

Note: check marks are used to indicate that a process was examined by the study in a column; comments in parentheses explain the different terms used by the study in a column; combined boxes indicate that the study placed several processes into a broad category.

5.2.1 PERSONALITY-BASED

Personality-based trust building mechanisms mean that people with different cultural backgrounds, personality types, and developmental experiences differ considerably in their general predisposition or tendency to trust others (Kramer, 1999; Mayer et al., 1995). They play an important role in the initial stage of a relationship when there are limited resources to judge other parties' trustworthiness (Gefen et al., 2003b; Mayer et al., 1995; McKnight et al., 1998; Rotter, 1971).

Dispositional process is personality-based. Dispositional process is triggered by the general tendency to trust or not to trust others (Gefen et al., 2003b; Mayer et al., 1995; McKnight et al., 1998; Rotter, 1971). Recent research found that disposition to trust is important in establishing interpersonal and organizational trust in e-commerce contexts as well as in building technology trust (Lee and Turban, 2001; McKnight et al., 2002a;

McKnight et al., 2004). Ample evidence exists from both laboratory studies and field studies that people differ significantly in their general tendency to trust others including technology (e.g., Kramer, 1999). Some people have a tendency to trust high technology systems while others do not (Komiak et al., 2005).

5.2.2 INSTITUTION-BASED

Institution-based trust building mechanisms are triggered by environmental structures that make an environment trustworthy (McKnight et al., 2002a; McKnight et al., 1998). With institution-based trust, people believe that necessary structures are in place to achieve a successful outcome. *Structural assurance* and *situational normality* are the two main institution-based trust building processes that are discussed in the literature (McKnight et al., 2002a; McKnight et al., 1998). Structural assurance refers to an assessment of trust based on contextual conditions such as regulations, guarantees, safety nets, promises, legal recourse, or other procedures that are in place (McKnight et al., 1998; Zucker, 1986). Situational normality refers to an assessment of trust based on a situation that is normal and in a properly ordered setting (Lewis and Weigert, 1985; McKnight et al., 1998).

Similar to the structural assurance, another process in this category is the *risk awareness process*. This process occurs when consumers are aware of potential risks in using the recommendation services in online environments. The existence of risks is one of the main reasons for the need of trust (Mayer et al., 1995). With regulations, guarantees or legal recourse, consumers face fewer risks, hence they are more likely to trust agents (Pennington et al., 2004). Inversely, being aware of risks (i.e., personal information leakage) in online environments reduces consumers' trust in agents. Consumers' perceived risk is quite high in the initial stage of relationship building due to the virtual nature of online environments and the lack of prior interaction history (Gefen et al., 2003b).

5.2.3 CALCULATIVE-BASED

Calculative process[19] occurs when consumers consider the costs of and/or the rewards for an agent acting in an untrustworthy way (Doney and Cannon, 1997; Gefen et al., 2003b; Lewicki and Bunker, 1995). When the benefits of acting in an untrustworthy manner (i.e., providing biased recommendations) exceeds the costs of being caught and penalized, consumers may infer that it would be contrary to the agent's benefit of acting in that way and thus the agent should be trusted (Akerlof, 1970; Gefen et al., 2003b). Gefen et al. (2003b) found that calculative based beliefs positively affect consumer trust in e-vendors.

5.2.4 HEURISTIC-BASED

Heuristic-based trust relies on first impressions or environmental cues rather than experiential interactions. It was termed as cognition-based trust by McKnight et al. (1998). They suggested two processes: 1) *categorization process* and 2) *illusions of control*, which apply to situations where consumers do not have prior first-hand experience with an agent.

Categorization process means that people put the other person in the same category as oneself, or place anther person into a general category of persons. People perceive others in a same group to be trustworthy because those who are grouped together tend to share common goals and values (Kramer et al., 1996). Also, people form positive trusting beliefs about the other by generalizing from the favorable category into which the person was placed (McKnight et al., 1998).

Illusions of control means that people try to assure themselves that things are under their personal control. In the interpersonal and organizational contexts, this process indicates that in an uncertain situation, people take small actions to try to influence others and test whether they are trustworthy (McKnight et al., 1998). McKnight et al. (1998) have suggested that such illusions of control help facilitate consumers' trust formation.

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[19] McKnight et al. (1998) considered this process as personality-based while other studies (e.g., Doney and Cannon 1997; Brashear et al. 2003) examined it as a situational factor. A pilot examination of the written protocols indicated that in most cases, this process is invoked by specific factors that related to the agent provider. Therefore, we included this process separate from the dispositional process.

This process also applies to consumer-agent relationship in that a recommendation agent is inanimate in nature and can be easily controlled by its users. Accordingly, some perceptions of control is not only illusions, but also real (Komiak, 2003). Because it involves agent-user interaction, we categorized it as a process based trust-building mechanism in section 5.2.5.

In addition to the above two processes, there are another two heuristic-based processes: 1) *transference process* and 2) *media assessment.*

Transference process was proposed by Doney and Cannon (1997) and empirically examined by Stewart (2003). Trust can be transferred from one entity or a credible proof source to others (Milliman and Fugate, 1998). When consumers interact with an agent for the first time, they identify other entities and heuristic cues closely associated with the recommendation agent (e.g., a general impression about the website or the reputation history of the e-vendor) to infer the agent's trustworthiness.

Media assessment process occurs when people evaluate an agent interface and the Internet media in determining their trust levels (Komiak, 2003; Komiak et al., 2005). A pleasant and easy to use interface indicates that a recommendation agent cares about users' effort and enjoyment in using the agent and invests its own effort in the commitment of the agent-consumer relationship (Gefen et al., 2003b). Consequently, perceived ease of use of an agent delivered in the Internet media influences consumers' trust levels in the agent.

5.2.5 PROCESS-BASED

Process-based trust formation was proposed by Zucker (1986). To determine their trust levels, consumers assess the other party's behavior and performance during their interactions. This mechanism consists of four processes (i.e., expectation confirmation, verification process, utility assessment, and control process).

Expectation Confirmation. Consumers use their expectations as a benchmark to judge the trustworthiness of online recommendation agents (Kramer, 1999). As Kramer (1999) suggested, "individuals' judgments about others' trustworthiness are anchored, at

least in part, on their *a priori* expectations about others' behavior" (p.576). Consumers trust an agent when they believe the agent behaves as they would expect (Gefen and Straub, 2003). When agents' actions do not conform to consumers' expectation, trust in the agents will be lower (Kramer, 1999; Lewicki and Bunker, 1995; Sitkin and Roth, 1993).

In the self-efficacy theory, Bandura (1997) has distinguished between two kinds of expectancy beliefs: outcome expectations – beliefs that certain behaviors will lead to certain outcomes (e.g., the belief that practice will improve one's performance), and efficacy and process expectations – beliefs about whether one can effectively perform the behaviors necessary to produce the outcome (e.g., I can practice sufficiently hard to win the next tennis match). Similarly, consumers have two types of expectations when using recommendation agents. One is outcome expectations, which are about the final recommendations (e.g., I should get several Olympus cameras). Consumers spend time and effort in using an agent, and thus, may expect to get a set of appropriate recommendations in return. When agent recommendations match the expectations, consumer trust emerges. Otherwise, consumer trust might decline. The other is process and behavior expectations, which are related to the activities that the agents should conduct in order to achieve certain outcomes (e.g., the agent should ask me about my brand preferences). Consumers may use their own knowledge to generate expectations regarding agent behavior. When an agent "behaves" in an expected way, consumers' trust in the agent will be higher.

Verification Process. This process has been proposed and validated in Komiak (2003) and Komiak et al. (2005). Being able to verify the performance of an agent with other resources greatly facilitate consumers' trust in the agent (Donnelly, 1994). In the initial relationship building, when consumers lack the knowledge to check the credibility of the agent and do not have an interaction history to rely on, they may consult a trusted third party (Komiak et al., 2005). For example, with their friends or product reviewers, consumers can verify whether or not the recommendations provided are good and whether or not the agent's claims are true. On the contrary, lack of means to check the advice from the agent makes the verification process difficult and it may inhibit

consumer trust. Verification process occurs especially when consumers have some doubts or suspicions about the agents so that they need to verify the advice from the agents with other sources (Komiak et al., 2005). The absence of a third party to verify will result in the lack of supporting evidence, hence the doubts and suspicions will remain (Donnelly, 1994), leading to trust deterioration and decline.

Utility Assessment. In a task-based context, utility assessment is one of the most important components of personal relationships and utility relationship with the most perceived valued will be characterized as being trustworthy in terms of competence and motive (Atkinson and Butcher, 2003). Extending this line of reasoning, we propose that the benefits gained from using the recommendation agents provide consumers with a foundation to judge the agent's competence and benevolence.

The causal relationship between trust and perceived usefulness has been modeled in different ways. For example, Koufaris and Hampton-Sosa (2004) advocated that perceived usefulness of a website influence consumers' initial trust in an online firm, while Gefen et al. (2003b) suggested that trust influences usefulness perceptions. In chapter 4, we also suggested that usefulness perceptions influence trust. The inclusion of the utility assessment process, which was identified in our pilot examination of the written protocols, is justified by the reciprocal influence of many psychological processes (Eagly and Chaiken, 1993). We agree that there might be psychological processes through which consumers' trust in the agents influences their utility assessment. Nevertheless, in the initial interaction with an agent, the utility that consumers gain from using the agent can be used as a basis for trust relationship building (Atkinson and Butcher, 2003). Consumers may generate an overall positive evaluation of the agent when they perceive it to be useful and such positive evaluation will reinforce and enhance their trust in the agent. The psychological processes of trust and utility assessments can be reciprocal and influence each other in the earlier stage of trust formation.

Control Process. In an organizational context, Luhmann (1979) and Das and Teng (1998) proposed a theory concerning the relationship between trust and control. Control mechanisms have an impact on trust because with proper control mechanisms, perceived

level of uncertainty is reduced and "the attainment of desirable goals becomes more predictable" (Das and Teng, 1998, p. 493). This uncertainty reduction principle applies in the initial stage to trust formation in online recommendation agents. With more control over an agent, consumes are less likely to be misguided by the agent and thus more likely to trust the agent (Komiak et al., 2005). As suggested in Silver (1991b), users' control over an agent involves the amount of choices provided by the agent, the tendency of the agent to influence consumer's decision making, and consumers' opportunity to express their needs, to list a few.

5.2.6 KNOWLEDGE-BASED

Knowledge-based trust relies on information about the trust target (Gefen et al., 2003b; Lewicki and Bunker, 1995). Trust develops when people gain knowledge about the other party (Gefen et al., 2003b), allowing them to interpret and predict the behavior of the other party (Doney and Cannon, 1997; Lewicki and Bunker, 1995). When interacting with an online recommendation agent, consumers have opportunities to understand and predict agent behavior utilizing information provided by the agent (Komiak, 2003; Komiak et al., 2005). Three processes are included in this cluster[20]: 1) information sharing process, 2) prediction process, and 3) "unknown" awareness process.

Information Sharing Process. As discussed in chapter 3, information asymmetry has been regarded as major obstacle to trust building due to the agency relationship between consumers and recommendation agents (Ba, 2001; Das and Teng, 1998; Donnelly, 1994; Hawkes et al., 1989; Whitener et al., 1998). Without sufficient explanation facilities, users lack information about agents' actions (i.e., procedures in generating recommendations) and motives (i.e., motivations in eliciting user requirements), leading to users' inability to verify agent competence and motivation. Trust is reduced when the other party behaves without explanation (Gefen and Straub, 2003). Openness and willingness to sharing information are important approaches to convey agent trustworthiness (Das and Teng, 1998; Whitener et al., 1998).

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[20] As shown in table 5-1, there are another three knowledge-based processes (i.e., competence, benevolence, and integrity assessment). Given that we define trust in recommendation agents to include competence, benevolence, and integrity beliefs. These three processes are tautological to the trust definitions, thus they were not included in this study.

Information sharing takes place when consumers get explanations regarding the agent's behavior, motivation, and so on. Gregor and Benbasat (1999) suggested that explanations are important components of intelligent systems, including online recommendation agents because, by making the performance of systems transparent to their users, they improve user trust in the systems. System transparency and understandability increase consumer trust in online recommendation agents (Aubert and Kelsey, 2003; Herlocker et al., 2000; Hertzum et al., 2002; Lee and Turban, 2001; Sinha and Swearingen, 2001; Sinha and Swearingen, 2002). Through appropriate explanations, consumers know more about the agent, better understand the agent's actions and thus can evaluate its competence, and are aware of the motivation and thus can evaluate the extent of benevolence. Information sharing also reduces the level of behavioral uncertainty, which, in turn, increase consumer trust (Kwon and Suh, 2004). In addition to such explanations, other information is needed as well, such as detailed product information which indicates that the agent is knowledgeable about a product (Komiak et al., 2005).

Prediction Process. In essence, the knowledge-based trust is grounded in the other's predictability (Lewicki and Bunker, 1995). The prediction process was empirically examined by Doney and Cannon (1997) in the context of buyer-seller relationships and by Brashear et al. (2003) in the context of manager-salesperson relationships. It concerns whether or not the agent is reliable, consistent, and predictable in consumers' eyes. When consumers are able to predict the agents' behavior (e.g., follow certain reasonable rules and be reliable), they may perceive the agent to be competent (as demonstrated by agent's use of certain rules) and to be less likely to take advantage of consumers. As a result, consumers will be more likely to trust the agent.

"Unknown" Awareness Process. This process was proposed and examined in Komiak (2003) and Komiak et al. (2005). In the initial relation building, different parties have limited knowledge about each other and might have difficulties to justify a high level of trust in others. Gambetta (1988) suggested that trust is particular relevant in conditions of ignorance with respect to unknown actions of others. When consumers are aware of some "unknown" about an agent, their trust in the agent will be lower. In contrast, when consumers have favorable perceptions of the agent's competence,

benevolence, and integrity, they will suspend worrying about the "known" (Komiak, 2003; Komiak et al., 2005). Therefore, this occurrence of this process inhibits consumer trust in an agent.

The above first six major clusters of trust formation mechanisms provide insights into how initial trust forms and expand Komiak (2003)'s trust formation scheme. Using a verbal protocol based process-tracing approach, Komiak (2003) and Komiak and Benbasat (2003) identified nine processes for agent trust formation. They explored the processes involved in the trust formation from the initial interaction between customers and a recommendation agent to the second and third interaction, and also examined the different processes for cognitive and emotional trust. Another similar study is Komiak et al. (2005), which compared the different trust-building processes in virtual recommendation agents versus real salespersons.

The present study is different from the aforementioned studies in several aspects. First, we employed a written protocol based rather than a verbal protocol based method (the methodological differences are addressed in section 5.3.1). Second, in addition to qualitatively coding the written protocols, a quantitative analysis was also conducted to test the predictive power of the main trust-building and trust-inhibiting processes in PLS. The above studies identified major processes by the frequency of various processes. However, the frequency of a process does not necessarily indicate its effect in forming consumers' trust perceptions. This study integrated an interpretive approach with a quantitative analysis, allowing us to further validate the major processes that influence consumers' trust levels in online recommendation agents. The advantages of combining qualitative and quantitative analysis approaches have been widely recognized (Kaplan and Duchon, 1988; Mingers, 2001). In this study, the multi-method approach minimizes the threat of mono-method variance, enables us to identify the cognitive processes rather than relying on self-reports only, and increases the robustness of results because the interpretative findings from the protocol analysis are further validated through a quantitative analysis.

Moreover, the recommendation agent investigated in the present study is provided and owned by the e-vendor while the agent in Komiak (2003) was assumed to be owned by consumers. Trust issues are more salient in this study because more uncertainties and risks are involved when consumers delegate their tasks to a recommendation agent owned by another entity. In such a situation, consumers may be more concerned about whether the agent works for the e-vendor or themselves.

5.3 RESEARCH METHOD

As described in chapter 3, after completing the experimental tasks, participants were surveyed regarding their trusting beliefs (i.e., quantitative data) and then were asked to answer several open-ended questions to justify their trust levels in the agents (i.e., qualitative data). The three essay questions relevant to this chapter are 1) *Do you believe the virtual advisor's competence? Why?* 2) *Do you believe the virtual advisor's benevolence? Why?* and 3) *Do you believe the virtual advisor's integrity? Why?* These three questions correspond to the three belief components (i.e., competence, benevolence, and integrity) of trust in online recommendation agents as defined in chapter 2.

5.3.1 WRITTEN PROTOCOL VERSUS VERBAL PROTOCOL ANALYSIS

We used a written protocol based method to elicit the reasons, processes, and factors that lead to consumers' trust development and decline in online recommendation agents (Todd and Benbasat, 1987). A variety of methods for process-tracing is available, such as verbal protocols, written protocols, computer logs, information display boards, and tracing of eye movements. Among them, the verbal protocol approach has been argued powerful because it provides the greatest data richness (Todd and Benbasat, 1987). For example, it provides access to what information is examined, and what analysis or assessment has been conducted by the problem solver. However, our choice of written protocols analysis is mainly because our interest is to investigate the underlying reasons and processes that lead to trust building and decline, rather than to reveal different activities that consumers conducted during the shopping tasks or to reveal the decision

strategies that consumers used to decide their shopping choices. As discussed in Todd and Benbasat (1987), verbal protocol analysis is appropriate for conditions where participants are required to report only the contents of short term memory (i.e., "what" the problem-solver /decision maker is doing, what info is using, and so forth). In contrast, written protocol analysis is appropriate for justifying why participants have performed in a certain way and justifying their overall evaluation of their experiences. Thus, written protocols were collected in this study.

5.4 DATA ANALYSIS

Each written protocol was broken into episodes (unit of coding) and each episode contained at most one trust-building or trust-inhibiting process. On average, each participant provided about six episodes total for the three essay questions. Around 65% of the episodes are related to trust-building processes and 35% of them are related to trust-inhibiting processes.

This study used a prior-research-driven and theory-driven approach to analyze the written protocols (Boyatzis, 1998). The process theories of trust formation reviewed earlier helped us interpret the protocols and guided us to identify the potential trust building and inhibiting processes in the written protocols.

A preliminary analysis of the written protocols culminated in a coding scheme having six clusters of trust building/inhibiting processes as informed by process theories of trust formation (i.e., personality based, institution based, calculative based, heuristic based, process based, and knowledge based). Each cluster of processes includes one or more individual processes. In total, 12 processes[21] were identified as potential trust building/inhibiting processes in online recommendation agents: 1) dispositional process, 2) risk awareness process, 3) transference process, 4) media assessment, 5) calculative

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[21] All of the 12 processes apply to both trust building and trust inhibiting. For some of them, the process for trust inhibiting should have been named in an opposite way (e.g., expectation disconfirmation, lack of information sharing). For the sake of simplicity in description, in most cases we only use the names of trust building to refer to both trust building and trust inhibiting.

process, 6) expectation confirmation, 7) verification process, 8) utility assessment, 9) control process, 10) information sharing process, 11) prediction process, and 12) "unknown" awareness process. The coding scheme with 12 processes and examples from the written protocols for each process are shown in table 5-2.

Three processes discussed in section 5.2 were not included in the coding scheme: 1) categorization process, 2) illusions of control, and 3) situational normality. The categorization process and illusions of control mainly apply to situations where consumers do not have prior first-hand experience with an agent (McKnight et al., 1998), while in this study participants interacted with an agent to get shopping advice. Our preliminary analysis did not find any protocols related to these two processes. Situational normality related protocols were not found either. Online recommendation agents are an emerging technology, thus currently many websites still do not provide online recommendation services. Therefore, we did not include situational normality in the coding scheme.

Two judges (the author and another research assistant) independently coded the protocols. For each episode, the judges decided on: 1) which process it belongs to, if any, and 2) whether it is trust building or inhibiting. Another column labeled "N" is used for those episodes that were coded as "no processes involved in."

Table 5-2 Trust Building/Inhibiting Processes and Examples		
Process	Source	Examples
Personality based		
1) Dispositional Process (DP)	Gefen et al. (2003); Mayer et al. (1995); McKnight et al. (1998); Rotter (1971)	Building: "I think that I do believe in the competence of the virtual advisor because well, I trust high-tech things."
		Inhibiting: "… However, in most websites, electronic advisors might be biased."
Institution based		
2) Risk Awareness Process (RK)	Komiak (2003); Mayer et al. (1995); Pennington et al. (2004)	Building: "… As well there is guarantee for purchasing the product."
		Inhibiting: "I don't feel so secure in using these services in a virtual environment."
Calculative based		
3) Calculative Process (CL)	Akerlof, (1970); Doney and Cannon (1997); Gefen et al. (2003)	Building: "… it has no reason to hide any information from me or to try 'push' a certain product to make a quick sale."
		Inhibiting: *(No instances were found)*
Heuristic based		
4) Transference Process (TR)	Doney and Cannon (1997); Stewart (2003); Milliman and Fugate (1998)	Building: "… and because I had good overall impression of the website."
		Inhibiting: "I would have some drawbacks on this because the online store doesn't really have a long reputation history."
5) Media Assessment (MA)	Komiak, 2003; Komiak et al. (2005)	Building: "Yes, because it is user-friendly and …"
		Inhibiting: "But a cartoon character might have been nicer; this virtual advisor is not 'physically attractive'."
Process based		
6) Expectation Confirmation (ET)	Kramer (1999); Komiak et al. (2005); Lewicki and Bunker (1995); Sitkin and Roth (1993)	Building: "Yes - because his recommendations match my expectations and prior knowledge of digital cameras."
		Inhibiting: "It would be better if the advisor can provide some outputs of the cameras so that the customers can really see the qualities of the cameras."
7) Verification Process (VF)	Donnelly (1994); Komiak et al. (2005)	Building: *(No instances were found)*
		Inhibiting: "I will also consult my friends who are familiar with digital cameras, as well as experienced digital camera salespeople for their further advice on the recommended models suggested by the virtual advisor."

Table 5-2 Trust Building/Inhibiting Processes and Examples (cont'd)		
Process	Source	Examples
Process based (cont'd)		
8) Utility Assessment (UT)	Atkinson and Butcher (2003)	Building: "... The advisor does provide a useful service."
		Inhibiting: "... but it wasn't as useful to the extent of a salesperson."
9) Control Process (CT)	Luhmann (1979); Das and Teng (1998); McKnight et al. (1998); Komiak et al. (2005)	Building: "... you can always change your answers if the camera they have chosen does not suit your needs."
		Inhibiting: "... I want to consider more choices when I am buying a digital camera."
Knowledge based		
10) Information Sharing Process (IS)	Gefen and Straub (2003); Das and Teng, (1998); Whitener et al. (1998); Komiak et al. (2005)	Building: "yes, the how explanations present me all his reasonable reasoning in choosing the cameras."
		Inhibiting: "... but I would like more explanation, so that people like me (who don't know anything about digital cameras) would benefit more."
11) Prediction Process (PD)	Lewicki and Bunker (1995); Doney and Cannon (1997); Brashear et al. (2003)	Building: "It'd get the job done by following all the steps prescribed, and get consistent results if the input information is the same."
		Inhibiting: "I don't think it is able to select the best product of the best price, except by random chance."
12) "Unknown" Awareness Process (UN)	Komiak, 2003; Komiak et al. (2005)	Building: *(No instances were found)*
		Inhibiting: "I do not know and therefore I am skeptical and try to make my own decisions (I try not to get persuaded)."

5.5 RESULTS

To assess the reliability of the coding scheme and ensure the validity of the analysis, Cohen's Kappa coefficient (Cohen, 1960) was used to measure the inter-coder agreement (Todd and Benbasat, 1987). The Kappa coefficient is 0.71, indicating the agreement between the two coders is substantial. Landis and Koch (1977, p.165) have suggested kappa ranging from 0.61 to 0.80 as a benchmark of high agreement. The average of the two judges' coding results was used for further analysis which aims at 1) identifying the

major processes for building and inhibiting trusting beliefs; 2) examining the differences in the processes for different trusting beliefs; 3) examining the differences in the processes of trust-building and those of trust-inhibiting for each trusting belief; and 4) testing the predictive power of the major processes on consumers' trusting belief scores.

The top five major trust-building processes and top five major trust-inhibiting processes for each trusting belief are listed in tables 5-3 and 5-4. For each process, the total numbers of episodes related to trust formation from all participants were summed up. Similarly, the total numbers of episodes related to trust decline from all participants were summed up. For each trusting belief, the top five building (or inhibiting) processes covers from 76% to 92% of all building (or inhibiting) processes for that belief from all participants. For all other processes, each counts for less than 6% of all building or inhibiting processes for a trusting belief, and accordingly was not considered as major processes.

Table 5-3 Major Trust-Building Processes			
Trusting Belief	**Competence**	**Benevolence**	**Integrity**
Process (%*)	Information Sharing (25%)	Expectation Confirmation (33%)	Expectation Confirmation (32%)
	Utility Assessment (25%)	Utility Assessment (14%)	Control Process (12%)
	Expectation Confirmation (25%)	Calculative Process (11%)	Prediction Process (12%)
	Prediction Process (10%)	Information Sharing (10%)	Information Sharing (10%)
	Transference Process (6%)	Control Process (9%)	Calculative Process (10%)

*: The percentage number = (total numbers of episodes related to a particular process leading to the formation of a particular trusting belief from all participants) / (total numbers of episodes related to the formation of a particular trusting belief from all participants and all processes)

Table 5-4 Major Trust-Inhibiting Processes			
Trusting Belief	**Competence**	**Benevolence**	**Integrity**
Process (%)	Expectation Disconfirmation (38%)	Expectation Disconfirmation (27%)	Dispositional Process (negative) (27%)
	Information Sharing (lack of) (21%)	Dispositional Process (negative) (21%)	Expectation Disconfirmation (24%)
	Dispositional Process (negative) (13%)	Transference Process (negative) (12%)	"Unknown" Awareness (20%)
	Verification Process (lack of) (8%)	"Unknown" Awareness (11%)	Information Sharing (lack of) (7%)
	Utility Assessment (negative) (8%)	Calculative Process (negative) (10%)	Calculative Process (negative) (7%)
			Transference Process (negative) (7%)

$\chi 2$ tests were used to examine the differential structures of different trusting beliefs in terms of building and inhibiting processes. $\chi 2$ tests were based on all the 12 processes. The results reported in table 5-5 indicate that different trusting beliefs are cultivated via different processes. According to table 5-3, only the information sharing and expectation confirmation processes appear in the top five building processes for all three trusting beliefs. As well, different trusting beliefs are inhibited via different processes. According to table 5-4, only the expectation disconfirmation and dispositional processes are among the top five inhibiting processes for all three trusting beliefs.

Table 5-5 $\chi 2$ Tests Comparing Processes for Different Trusting Beliefs		
Building/Inhibiting	χ_{22}^2	p value
Building	61.7	<.0001
Inhibiting	44.3	0.003

χ^2 tests based on all the 12 processes were also used to examine the differences in the building processes versus inhibiting processes for each trusting belief. The χ^2 test results in table 5-6 indicate that the building processes are statistically different from those inhibiting processes for each trusting belief.

Table 5-6 $\chi 2$ Tests Comparing Trust Building vs Trust Inhibiting Processes		
Trusting Beliefs	χ_{11}^2	p value
Competence	40.3	<.0001
Benevolence	39.3	<.0001
Integrity	52.9	<.0001

To further examine the power of the major trust-building and trust-inhibiting processes in predicting consumers trust beliefs, a PLS analysis was performed. The unit of analysis is each participant. For each participant, the numbers of the major processes for trusting-building and those for trust-inhibiting were used as input. The multi-item trusting belief measures were modeled as reflective indicators of their corresponding latent constructs, which were used as dependent variables in PLS. Three separate PLS analyses were conducted, with one for each trusting belief.

PLS is especially suitable for exploratory studies in the stage of theory building (Barclay et al., 1995). PLS was chosen also because it does not require normal distribution of data for estimating parameters. The numbers of episodes for one particular process from any one participant is between 0 and 2, and are not normally distributed.

The measurement items and measurement validation for the trusting beliefs is described in chapter 4. The PLS results including the significant path coefficients and the significance levels are shows in figures 5-1, 5-2, and 5-3 for competence, benevolence, and integrity, respectively. The results reveal the relatively predictive power of different processes on the trusting belief scores. Information sharing, expectation confirmation, and utility assessment processes significantly contribute to the formation of competence belief, while expectation disconfirmation, lack of information sharing, utility assessment, and verification processes lead to the decline of competence belief. Expectation confirmation, calculative process, utility assessment, and control processes significantly induce benevolence belief, while only "unknown" awareness processes inhibit benevolence belief. Expectation confirmation, prediction process, and dispositional processes significantly increase integrity belief, while "unknown" awareness processes, calculative process, and transference processes significantly reduce integrity belief.

*** p<.01, ** p<.05 (bootstrap method);
Only significant paths are shown.
Processes in white boxes build trust while those in the black boxes
inhibit trust.

Figure 5-1 PLS Results for Competence Belief

*** p<.01, ** p<.05 (bootstrap method);
Only significant paths are shown.
Processes in white boxes build trust while those in the black boxes
inhibit trust.

Figure 5-2 PLS Results for Benevolence Belief

*** p<.01, ** p<.05, * p<.1 (bootstrap method);
Only significant paths are shown.
Processes in white boxes build trust while those in the black boxes
inhibit trust.

Figure 5-3 PLS Results for Integrity Belief

5.6 DISCUSSION

5.6.1 SUMMARY OF FINDINGS

Trust formation in online recommendation agents is an under-studied area. Applying both qualitative and quantitative analyses, this study explored consumers' initial formation processes in recommendation agents. Using a prior-research driven approach, Komiak (2003)'s trust formation scheme was revised in this study according to the interplay of the process theories of initial trust formation (e.g., Lewicki and Bunker, 1995; McKnight et al., 1998) and the written protocols collected in this study. The major processes for

promoting and hampering consumers' trusting beliefs in online recommendation agents were identified. These major processes explained a significant portion of variances in the trusting belief scores (see figures 5-1, 5-2, and 5-3).

The results reveal different formation processes for different trusting beliefs. Although some processes (i.e., expectation confirmation) are important for all three trusting beliefs, there are certain processes that only relate to particular trusting beliefs. For example, the "unknown" awareness processes mainly lead to the decline of benevolence and integrity, while information sharing processes are most influential for competence belief formation and its reduction, and dispositional processes only contribute to inhibiting the integrity belief. These results indicate that consumers form different trusting beliefs in different ways and also lend support to the fact that different trusting beliefs exist in the initial stage of trust formation (McKnight et al., 2002a).

The written protocols confirm that consumers' trust building and inhibiting processes co-exist in the initial formation stages (Cacioppo and Berntson, 1994; Cenfetelli, 2004). There are some processes that contribute to both trust-building and trust-inhibiting in online recommendation agents. For example, expectation confirmation increase consumer competence belief in an agent and expectation disconfirmation leads to the decline of competence belief; utility assessment both facilitates and inhibits competence belief. But many processes' impacts are asymmetric. For example, calculative processes, expectation confirmation, utility assessment, and control processes only increase consumers' competence belief while they do not decrease it. Inversely, the "unknown" awareness processes only lead to benevolence decline, but not increase the benevolence belief.

5.6.2 LIMITATIONS AND FUTURE RESEARCH

In addition to the limitations discussed in chapter 3, this chapter has another two limitations. First, the experimental tasks did not involve real purchases although we asked participants to treat the experimental tasks as if they were real. Participants were only asked to *decide* what camera models to buy for the tasks with the support from a recommendation agent. Future research is needed to examine the trust formation

processes in a real shopping environment, where consumers' risk and trust perceptions might be stronger and as a result, different processes might be involved in.

Second, the written protocol method also has some limitations. We used retrospective protocols (i.e., protocols were collected after the experimental tasks). The advantage of using written protocols rather than verbal protocols is that the elicitation of textual narratives does not interfere with the ongoing consumer-agent interactions during the experimental tasks (Todd and Benbasat, 1987). But it requires participants' recall of their cognitive processes formed earlier and participants may systematically reorganize their perceptions and cognitions (Todd and Benbasat, 1987). Additionally, the essay questions used to elicit the written protocols may have cause participants to be more self-reflective about their trust beliefs formation than usual (Gould, 1997). Nevertheless, aided with the PLS analysis, the most powerful and influential processes from the protocol analysis are further validated with evidence and should be valid.

The research identified several trust formation processes that have been largely ignored in the literature. The results show that process-based and knowledge-based mechanisms (e.g., expectation confirmation, utility assessment, information sharing, "unknown" awareness processes) play in important roles in trust formation in online recommendation agents. However, few studies have focused on these important processes, which deserve future research.

5.6.3 THEORETICAL AND PRACTICAL IMPLICATIONS

This study makes significant contributions to research and practice. The main contribution to research is that it enriches the trust theory by revealing the trust formation processes in recommendation agents for online shopping. Trust in online recommendation agents is an important issue in that it directly influences users' adoption of the agents (Komiak, 2003, see also chapter 4). Prior trust research mainly focused on interpersonal and organizational trust. This study bridges the gap in the understanding of trust formation in technology artifacts including online recommendation agents.

Furthermore, this study identified an asymmetric formation structure of trust building and inhibiting processes. Cenfetelli (2004) has considered inhibitors and enablers as dual factors in technology usages and called for researched into the inhibiting perceptions. In the interpersonal and organizational contexts, the fragile nature of initial trust has been known for ages (Lewicki and Bunker, 1995). McKnight et al. (1998) discussed the conditions under which trust could be fragile or robust. To sustain consumers' trust in online recommendation agents, we need to not only focus on the trust building processes but also those processes that lead to trust deterioration and decline (Lewicki and Bunker, 1995).

This study has important practical implications for the design of trustworthy online recommendation agents. This research reveals that overall the most important processes for trust building include expectation confirmation, utility assessment, and information sharing processes, while the most influential processes that lead to trust decline include "unknown" awareness processes and expectation disconfirmation. Different processes can be engendered by different agent design features and functionalities.

Expectation confirmation. Understanding and meeting consumers' expectations facilitate trust-building in online recommendation agents and expectation disconfirmation inhibits consumers' trust. As deduced from the written protocols, participants with different levels of product expertise expect an agent to behave in different ways. Participants with a low level of expertise expected the agent to ask questions related to basic features of cameras while those with a high level of expertise expected the agent to elicit their requirements on both basic and advanced features. Accordingly, the agent-user dialogues should be designed in a personalized way that different types of questions and different levels of sophistication should be used for different segments of consumers (Russo, 2002).

A second solution is that recommendation agents should elicit the importance levels of consumers' different preferences and take them into account when making recommendations. These importance levels reflect consumers' expectation of the priority

of their preferences that the agents should consider and the recommended products should satisfy. Consumers would expect to get the recommendations with most important features.

A third solution is that recommendation agents should be able to provide more product recommendations upon consumers' request. Consumers spend time and effort in interacting with the agents and in return, they expect to see a certain number of recommendations. When few suitable products are recommended according to consumers' preferences, consumers should be able to get more recommendations, even sub-optimal, or other products (e.g., best sellers) should be recommended (Aggarwal and Vaidyanathan, 2003). Our written protocols indicate that the expectation disconfirmation process occurred when no or very few recommendations were provided.

Information sharing. As discussed in chapter 3, this process can be prompted by the explanation facilities provided by recommendation agents. This chapter provides additional evidence regarding the impact of explanation facilities on consumers' trust formation in online recommendation agents. We compared the group of subjects in the condition of "with" explanations to those in the "without" explanation condition, and found that when explanations are available, the number of episodes that are related to knowledge-based processes for trust-building increased nearly four-fold (i.e., from 3.5 to 16.5) while the number of trust-inhibiting episodes dropped from 17 to only 1. This confirms the important role of explanation facilities in promoting knowledge-based trust-building processes and reducing trust-inhibiting processes.

Accordingly, an agent should inform consumers what and how it performs and why it does in a certain way so that consumers can better understand the agent behavior, and it should also provide consumers with necessary knowledge and guidance so that consumers can make informed choices in the consumer-agent dialogues. The explanations make the agent more open, understandable, and considerate in consumers' eyes. Additionally, consumers need detailed product information, and experts' and other consumers' comments on the recommended products. Such information provides a

foundation for consumers to judge the agent ability, intentions, and integrity, and facilitates their trust in an agent.

Utility assessment. One of the major benefits of using recommendation agents is to facilitate consumers' decision-making. One weakness of current agent applications is that consumers' power to evaluate product recommendations is limited. One solution is to embed multimedia technologies into agent applications to facilitate consumers' product evaluation and preference expression. Using virtual reality technology together with recommendation agents enables consumers not only to express their preference and get recommendations, but also to evaluate the product recommendations and construct their preferences. It can greatly facilitate consumers' decision-making. Such an approach will deliver more utility and benefits for users. Jiang, Wang, and Benbasat (forthcoming) proposed a multimedia-based interactive advising technology that embed the user-agent dialogues into virtual reality enabled product images.

"Unknown" awareness process. When consumers do not have sufficient interactions with or information about online recommendation agents, they will have difficulties in judging the trustworthiness of the agents. Then, the "unknown" awareness process will be invoked. The explanations mentioned earlier may also help lessen such "unknown" awareness. As deduced from the written protocols, feedback about the agents from other consumers can be a source to supply additional information about the agents. Providing a discussion forum about an agent can elicit feedback on the agent. The forum should allow consumers to ask questions about an agent and get answers from other consumers as well as to provide comments about the agent to share with others. These additional functionalities help reduce the "unknown" awareness processes and consequently, prevent trust decline and deterioration.

By incorporating various agent features and capabilities that can promote the trust-building processes and reduce the trust-inhibiting processes, recommendation services in online environments could be more effective and gain higher chance of use adoption. Consumers' online shopping can be facilitated by an interface with a

trustworthy recommendation agent that guides and directs customer choices, leading to more positive online shopping experiences (Grenci and Todd, 2002).

CHAPTER 6: IMPACT OF DECISION STRATEGY SUPPORT AND EXPLANATION FACILITIES ON TRUST AND ADOPTION OF ONLINE RECOMMENDATION AGENTS

6.1 Overview

Online recommendation agents help consumers reduce information overload and improve decision quality (e.g., Haubl and Trifts, 2000; Maes, 1994), but they also restrict consumers to using only those decision processes that are supported by the agents (Silver, 1990). Silver (e.g., 1988) introduced the concept of agent restrictiveness which refers to the extent to which a recommendation agent limits its users' choices and decision-making processes. Agent restrictiveness has been suggested to be an important factor influencing user perceptions and evaluations of an agent (Silver, 1988; 1990; 1991b). When a consumer's desired decision strategies are not supported by an agent, the agent is perceived to be restrictive, and the final recommendations may not fit the consumer's preferences. As a result, the consumer may have a negative perception of the agent and may not trust it. However, few studies have investigated the impact of agent restrictiveness on consumers' trust and the adoption of online recommendation agents.

In this chapter, the role of agent restrictiveness in influencing consumer trust and adoption of online recommendation agents is examined. Agent restrictiveness is manipulated by different levels of decision strategy support provided by an agent. An agent with a high level of decision strategy support allows consumers to express their preferences for decision strategies and would be perceived as being less restrictive. Further, to effectively choose their decision strategies, consumers should be able to understand the strategies supported by the agent and how the agent works (Beaulieu and Jones, 1998; Dhaliwal and Benbasat, 1996). Therefore, the role of agent transparency (i.e., the extent to which an agent can be easily understood) is also examined. Since explanation facilities have been suggested to be effective in increasing agent transparency (Gregor and Benbasat, 1999), this study examines how explanations help consumers best utilize the decision strategy support functionality.

In addition, utilizing the strategy support functionality provided and a user's choice of decision strategies lead to different levels of cognitive effort (Todd and Benbasat, 1999). According to the cognitive effort perspective in behavioral decision theory (e.g., Payne et al., 1993; Todd and Benbasat, 1992) and the notion of Production Paradox (Carroll and Rosson, 1987), the consumers' preferences for effort vs. decision accuracy play an important role in their use of an agent's capabilities, both influencing their evaluations and acceptance of a recommendation agent. Consumers may not bother spending extra effort learning about an agent or trying its additional features. Thus, the role of cognitive effort is also examined.

A second laboratory experiment was conducted to investigate the above issues. The results confirm the presence of a significant impact of perceived agent restrictiveness on consumers' trust in recommendation agents, and reveal the relative effects of perceived agent restrictiveness, perceived agent transparency, and perceived cognitive effort on consumers' trust and intentions to adopt the agents. This study also shows that, to make the decision strategy support functionality effective, explanations should be provided and the cognitive effort involved in utilizing the decision strategy support should be minimal. Otherwise, the decision strategy support functionality may not be effectively utilized.

This chapter contributes to research by understanding the role of perceived agent restrictiveness, perceived agent transparency, and the cognitive effort in influencing consumers' trust and adoption of online recommendation agents. Both the benefits and costs of decision strategy support provided by online recommendation agents are examined, and the design implications are discussed.

The remainder of this chapter is organized as follows. Section 6.2 discusses the theoretical background for the current study. Section 6.3 develops hypotheses. The research method and results of hypothesis testing are reported in sections 6.4 and 6.5, and the chapter concludes with a discussion of the results, limitations, and contributions of the study and some future research areas.

6.2 Theoretical Background

6.2.1 PREFERENTIAL CHOICE STRATEGIES

In this study, product recommendation agents are utilized to help consumers make choices in the context of a multialternative, multiattribute preferential online shopping task (Keeney and Raiffa, 1976). Such tasks require decision-makers to choose one product among a number of alternatives available in an online store, or across a variety of online stores. Each alternative is described by a common set of attributes. Svenson (1979) describes 12 strategies that are applicable to preferential choice problems. Among them, Additive Compensatory (AC) and Elimination by Aspect (EBA) are the two most commonly studied strategies (e.g., Jarvenpaa, 1989; Payne, 1976; Todd and Benbasat, 1999; 2000), which are applicable to online recommendation agents (e.g., Pereira, 2000; Tan, 2003).

The AC strategy is a compensatory strategy. It is based on the evaluation of one alternative at a time with regard to all relevant attributes. Each attribute is assigned a weight indicating the importance level of the attribute. A score for each alternative is determined by summing the products of each attribute's transformed (i.e., normalized) value and weight. Once the computations are completed for all alternatives, the one with the highest weighted total score is chosen. In applying the EBA strategy, all alternatives are evaluated along one attribute and any alternatives that violate the threshold value for that attribute are eliminated. This process is repeated for each attribute until a single alternative remains. For the EBA strategy, lower value attributes are not compensated with higher value ones, hence, good alternatives might be eliminated prematurely. The AC strategy, in contrast, allows high value attributes to compensate for low value ones. Therefore, the decision quality of the AC strategy is superior to that of EBA strategy and the AC strategy is regarded as a normative strategy (e.g., Payne et al., 1993; Todd and Benbasat, 2000).

6.2.2 THEORY OF SYSTEM RESTRICTIVENESS

The use of online recommendation agents restricts consumers to certain decision processes that are supported by an agent (Silver, 1990). In the context of DSS, Silver (1990) defines system restrictiveness as the extent to which, and the manner in which, a DSS limits users' choices and decision-making processes. Since a DSS provides various operators (e.g., arithmetic functions) to facilitate users' decision-making, the restrictiveness of a DSS is determined by the factors related to these operators. Silver (1991a) suggested that a DSS can limit decision-making processes by restricting the: 1) set of operators available, 2) inputs to the operators (data, parameters, and control values), 3) outputs from the operators (representations), 4) sequencing of operators, and 5) modification and creation of operators.

In the context of needs-based recommendation agents, consumers interact with recommendation agents via other means (e.g., agent-user dialogues) that can express their needs and preferences. Accordingly, for online recommendation agents, the five ways of influencing agent restrictiveness, mentioned above, are adapted to: 1) questions in the dialogue, 2) possible replies to the questions, 3) outputs / recommendations after answering the questions, 4) sequencing of the questions, and 5) decision strategies.

All Possible Processes

All Supported Processes

All Possible Strategies

All Supported Strategies

(a): DSS   (b): Recommendation Agents
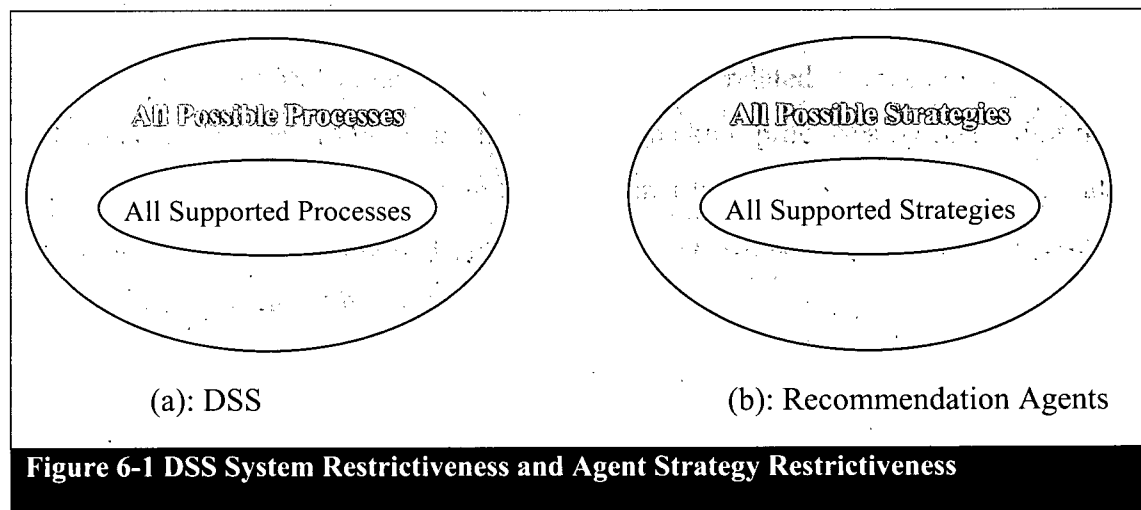
Figure 6-1 DSS System Restrictiveness and Agent Strategy Restrictiveness

This study focuses on the last aspect of restrictiveness that is related to decision strategies. Based on the depiction of DSS restrictiveness in figure 6-1a (Silver, 1991a), the restrictiveness of the decision strategy of the recommendation agents refers to the extent to which all possible decision strategies are supported by the agents (figure 6-1b).

Silver (e.g., 1988; 1991b) suggested that the perceived restrictiveness of an agent varies from one user to another. Subjective restrictiveness is determined by how users perceive the set of possible and supported decision-making processes. When an agent provides support for certain decision-making processes, users who prefer these processes perceive the agent to be less restrictive than those who do not prefer the processes. Therefore, what matters for the consumers' evaluations of an agent is the subjective restrictiveness of the agent.

Silver also discussed the level of restrictiveness that a system should offer (e.g., Silver, 1990). With excessive restrictiveness (i.e., a DSS provides very limited support for decision-making), most preferred decision processes are not supported by the DSS, hence, consumers may choose not to use the system. On the contrary, with too little restrictiveness, a system may overwhelm the user by presenting a large number of different capabilities (e.g., many strategy options and parameters) so that users may not be able to effectively choose among the many features. Therefore, although reducing agent restrictiveness has a positive influence on the agent's quality (Halloran et al., 1978; Nelson et al., 2005; Swanson and Ramiller, 1987; Wang and Strong, 1996), the agent should be carefully designed so that the agents' capabilities may be effectively utilized by users. Factors need to be considered including the understandability of an agent (e.g., Silver, 1990) and users' effort in using agent capabilities (e.g., Todd and Benbasat, 1999).

6.3 Hypotheses Development

This study compares three types of recommendation agents that implement different decision strategies. In addition to the AC-based and EBA-based agents, a new type of recommendation agent that uses a hybrid strategy is proposed (supporting both AC and

EBA strategies, see section 6.3.1). Consumers' perceived restrictiveness of the three types of agents is hypothesized to be different (see section 6.3.2). The relative levels of perceived agent transparency and cognitive effort in using the three types of agents are also examined (see section 6.3.3 and 6.3.4). Hypotheses are also presented to study the interaction effects between the explanation facilities and the decision strategy support on perceived restrictiveness and perceived transparency (see section 6.3.3). In addition, the impacts of these perceptions on trust and the antecedents of user acceptance of an agent in TAM (i.e., PU and PEOU) are evaluated. Finally, the Trust-TAM model is tested (see section 6.3.5). The research model is depicted in figure 6-2.

Note: +, −, and × indicate a positive, negative, and interaction
relationship, respectively; 0 indicates no predicted significant correlation.
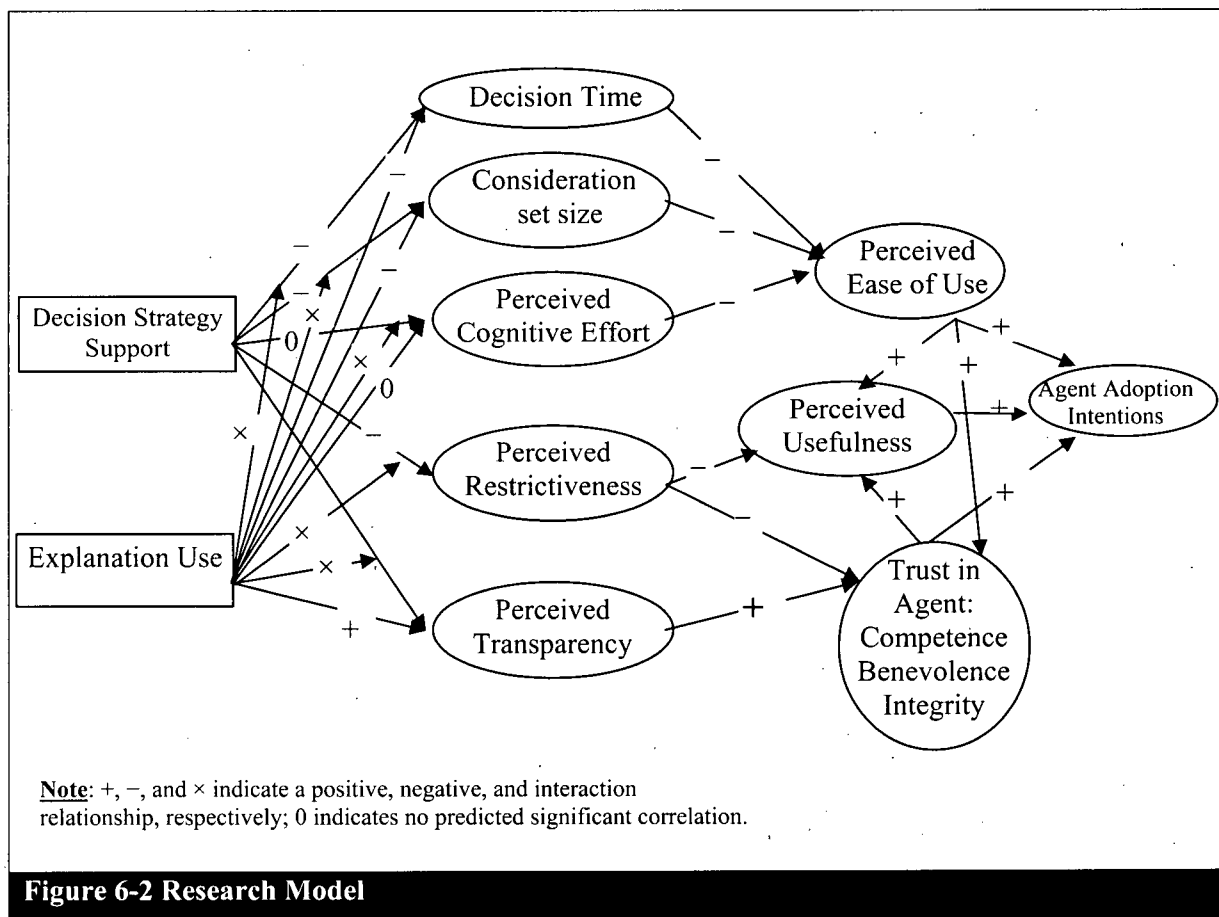
Figure 6-2 Research Model

6.3.1 RECOMMENDATION AGENTS WITH DIFFERENT LEVELS OF DECISION STRATEGY SUPPORT

As described in section 6.2, the AC-based and EBA-based recommendation agents (hereafter, referred to as AC agents and EBA agents, respectively) only apply one choice strategy. As implemented in Experiment 1, both AC and EBA agents in this study utilized agent-user dialogues to elicit user needs and preferences. The agents first determine the product features or attribute levels inferred from consumer preferences and then evaluate the available products using the inferred product features or attribute levels (Russo, 2002). When an alternative does not have an inferred product feature or does not fit an inferred attribute level, for the AC agents the fit score of the alternative is deducted by the product of the importance weight and the gap between the user requirement and the level that the alternative can satisfy[22], while the EBA agents eliminate the alternative from further consideration.

This study proposes a new type of recommendation agent using both AC and EBA strategies, namely, the Hybrid agents. When answering each question in the agent-user dialogue to express preferences, consumers can choose whether or not the preference can be traded-off by others. This was implemented by asking participants if their preference was essential or non-essential (refer to figure A6-1(a) in appendix 6-1). When participants chose "non-essential," an importance level was identified by a 9-point scale (refer to figure A6-1(b) in appendix 6-1). For the set of "essential" preferences, the EBA strategy was applied. For the set of "non-essential" preferences, the AC strategy was applied.

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[22] The formula used to calculate the fit score is as follows.

$$\text{Fit Score} = 100 - \sum_{i=1}^{r} (\text{Importance\_Weight} \times \text{Attribute\_Needs\_Gap})$$

r is the number of questions in the agent-user dialogue. To simplify the calculation, three levels of Attribute_Needs_Gap were used. When a product attribute (or feature) satisfies user needs (or preference), the Attribute_Needs_Gap equals 0. Otherwise, it equals either 1 or 2 depending on the size of the gap between the attribute levels and user needs and preferences. For example, if a consumer prefers a small size camera, for medium size cameras the Attribute_Needs_Gap equals 1 and for large size cameras it equals 2, while for small size cameras it equals 0.

6.3.2 ROLE OF AGENT STRATEGY RESTRICTIVENESS

6.3.2.1 IMPACT OF DECISION STRATEGY SUPPORT AND EXPLANATION FACILITIES ON PERCEIVED AGENT STRATEGY RESTRICTIVENESS

According to Silver's theory of system restrictiveness, the users' perceptions of restrictiveness are determined by the extent to which the preferred decision processes are supported. The difference between the Hybrid agents and the two other types (AC agents and EBA agents) is that the Hybrid agents support both AC and EBA strategies while the other two support only one strategy. As suggested by Todd and Benbasat (2000), "in practice, individuals typically employ hybrid strategies as opposed to pure approaches" (p. 96). This is especially true in online shopping environments where a large number of alternatives are available in an online store or across a variety of stores. Applying the EBA strategy can easily reduce the number of alternatives, but frequently, a null recommendation set is obtained as good alternatives might be eliminated prematurely (Tan, 2003). On the other hand, the AC strategy can produce a list of good alternatives with a fit score for each, but may present too many alternatives to consumers. Hybrid agents thus are desirable because the appropriate use of both AC and EBA strategies not only reduces the number of alternatives but also retains the alternatives with high overall quality.

Silver (1988) investigated user perceptions of system restrictiveness of DSS with different types and amounts of supporting operators (e.g., Data Sort) that users can choose and control over. Silver compared three types of DSS, namely, "Lotus 1-2-3," "Multi-Attribute-Software System" (MASS), and "Elimination by Aspector." The "Elimination by Aspector" applied a single choice rule (i.e., "elimination by aspects"), which is a subset of decision rule that is supported by MASS, while MASS applied a subset of the choice rules supported by "Lotus 1-2-3." Silver found that users' perceptions of restrictiveness overall were lower when more decision rules were supported by a DSS. Similarly, by supporting both EBA and AC strategies that consumers can choose and control over, Hybrid agents will be perceived as being less restrictive than either AC agents or EBA agents. For AC agents and EBA agents,

consumers' perceived restrictiveness should be in a similar level, because each implements one strategy. Therefore, we hypothesize that:

H6-1a: Hybrid agents will be perceived to be less restrictive than AC agents.

H6-1b: Hybrid agents will be perceived to be less restrictive than EBA agents.

H6-1c: AC agents will be perceived to be as restrictive as EBA agents.

In addition to the availability of different strategies that are supported by recommendation agents, consumers should understand the agents' decision strategy support capabilities before using them fully (Silver, 1988). Hybrid agents provide consumers with control over the agent strategies rather than pre-determining them, as do AC and EBA agents. To effectively exercise the control, consumers need a good mental model of the agents and the agent features should be clearly explained (Beaulieu and Jones, 1998).

If consumers cannot understand the differences between the strategies provided by a Hybrid agent, or how the different strategies are used by the agent, they may not choose the strategies they want to employ. Therefore, perceived restrictiveness of a Hybrid agent depends on whether or not consumers understand the range of strategies that are supported. Without explanations, consumers may not realize the strategy options provided by a Hybrid agent, and thus, their perceived restrictiveness levels for Hybrid, AC, and EBA agents will be similar. Therefore,

H6-2a: With explanation use, Hybrid agents will be perceived less restrictive than AC or EBA agents; AC agents will be perceived as to be restrictive as EBA agents.

H6-2b: Without explanations, Hybrid agents will be perceived to be as restrictive as AC and EBA agents.

6.3.2.2 IMPACT OF PERCEIVED STRATEGY RESTRICTIVENESS ON TRUST AND PERCEIVED USEFULNESS OF AGENTS

Consumers' perceived restrictiveness in an agent influences their attitudes, beliefs, and other perceptions toward the agent (Silver, 1991a). This study focuses on the two major antecedents of user adoption of online recommendation agents in Trust-TAM: 1) trust in the agents and 2) perceived usefulness (PU) of the agents.

Online recommendation agents with low perceived strategy restrictiveness allow consumers to more freely express their decision strategy preferences. Thus, consumers perceive agents to be similar to themselves, in terms of the decision strategies that can be utilized. Prior research shows that similarity plays an important role in persuasion, and that people who are perceived to be similar to their audience are more influential in changing attitudes and beliefs (Komiak, 2003; Miller, 1984; Simons et al., 1970). Earle and Cvetkovich (1995) and Stewart (2003) also suggested that people tend to trust others who are similar to themselves. In the context of human-computer interaction, Nass and Lee (2001)'s results demonstrate that users trust a computer more if they perceive that its personality is similar to their own. Therefore, reducing the perceptions of agent restrictiveness is posited to enhance consumers' trust in an agent.

The perceptions of low agent restrictiveness can also facilitate consumers' trust in a recommendation agent via two other mechanisms: 1) empowering consumer control over the agent, and 2) confirming consumers' expectations (Komiak, 2003; Komiak et al., forthcoming). In an organizational context, Luhmann (1979) and Das and Teng (1998) proposed a theory for the relationship between trust and control. User control has an impact on trust because, with proper control mechanisms, the perceived level of uncertainty is reduced (Luhmann, 1979) and "the attainment of desirable goals becomes more predictable" (Das and Teng, 1998, p. 493). Whitener et al. (1998) also found that in the organizational context, "participation in decision-making and delegating control are key components of trustworthy behavior" (p. 517). Low agent restrictiveness means that consumers have more control over the agent by deciding which strategy should be employed, thus it facilitates consumers' trust in an agent.

Expectation confirmation means that when an agent behaves in a way as consumers expect, trust in the agent increases (Komiak et al., forthcoming). Low agent restrictiveness, i.e., an agent's ability to adapt its decision strategies according to the wishes of consumers, enables the agent to find suitable products in a way that is expected by the consumer, thus it increases consumers' trust. Therefore, it is hypothesized that:

H6-3: Perceived agent restrictiveness will negatively influence consumers' trust in online recommendation agents.

Perceived agent restrictiveness can also influence other antecedents in TAM, such as the PU of an agent. The PU of an agent is determined in part by the utility that consumers can get from the use of the agent (Davis, 1989). The utility of using a recommendation agent comes from: 1) narrowing down the alternatives so as to reduce the consumer's effort to examine them (Tan, 2003), and 2) finding good recommendations that are based on consumer preferences, including their needs and strategy preferences (Komiak, 2003). As mentioned earlier, by using both the EBA and AC strategies, an agent can effectively reduce the number of alternatives and also retain the good alternatives. Lower agent restrictiveness provides consumers with an opportunity to more freely express their strategy preferences. As a result, the recommendations from the agent will better cater their needs and preferences and the final recommendations will be more suitable, hence the agent will be perceived as being more useful. Therefore, it is hypothesized that:

H6-4: Perceived agent restrictiveness will negatively influence consumers' PU of online recommendation agents.

6.3.3 ROLE OF PERCEIVED AGENT TRANSPARENCY

Providing high decision strategy support allows consumers to make choices in decision strategies and reduces their perceptions of agent restrictiveness. Nevertheless, reducing agent restrictiveness can be a double-edged sword (Silver, 1990). If too many choices and functionalities are provided by an agent, the agent becomes complicated to use, and it is more difficult for consumers to understand how it works (Silver, 1990).

6.3.3.1 IMPACT OF DECISION STRATEGY SUPPORT AND EXPLANATION FACILITIES ON PERCEIVED AGENT TRANSPARENCY

The notion of system transparency has been mentioned in many previous studies (Gregor and Benbasat, 1999). According to the Merriam-Webster Dictionary, transparency means being easily detected, readily understood, or seen through. Sinha and Swearingen (2001) surveyed transparency levels of various online music recommender systems. They found that users perceived different systems to be very different in system transparency and that their confidence and preference of a system were closely related to their perceptions of system transparency.

In an earlier study, Montgomery and Benbasat (1983) suggested that the sophistication of a computer system influences its transparency. If users can easily understand the process of recommendation generation, they will perceive the system as being more transparent (Herlocker et al., 2000). A sophisticated agent is difficult to understand, thus it is less transparent to users. Increased agent functionalities (e.g., choosing from different decision strategies rather than using a single pre-determined strategy) may increase the difficulty for consumers to understand the recommendation-making processes, as the strategies employed by the agents become more complex. This will reduce agent transparency.

To compensate for these side-effects caused by high decision strategy support, explanations are used to increase the agent transparency (Gregor and Benbasat, 1999; Herlocker et al., 2000; Muramatsu and Pratt, 2001). As examined in chapter 3, explanation use increases consumers' trust in recommendation agents, though the mediating role of transparency has not been investigated. Explanations inform agent users about, for example, what the system does, how it works, and why its actions are appropriate (Gregor and Benbasat, 1999), and facilitate the consumers' understanding of an agent. Therefore, it is hypothesized that:

H6-5: Use of explanations will increase consumers' perceived agent transparency of online recommendation agents.

With these considerations in mind, if a Hybrid agent does not provide explanations, it will be perceived to be less transparent than the AC or EBA agents; while AC agents will be perceived to be as transparent as the EBA agents since both types employ one decision strategy.

Moreover, when the decision strategies deployed by Hybrid agents include both EBA and AC strategies, agent behaviors and motivations can be well explained with a set of appropriate explanations (Herlocker et al., 2000), thus the recommendations will be easily understood. For complex systems, consumers will use explanations for learning and understanding purposes (Gregor and Benbasat, 1999). As a result, with explanation facilities, agent transparency can be maintained. That is, regardless of whether a single strategy or a hybrid strategy is employed, perceived agent transparency will remain high when the agent provides consumers with detailed explanations. An interaction will occur between explanation facilities and the agent decision strategy support. Therefore,

H6-6a: With explanation use, Hybrid agents will be perceived as being equally transparent as AC agents or EBA agents.

H6-6b: Without explanations, Hybrid agents will be perceived to be less transparent than AC agents or EBA agents; AC agents will be perceived to be equally transparent as the EBA agents.

6.3.3.2 IMPACT OF PERCEIVED AGENT TRANSPARENCY ON TRUST

A transparent agent means that consumers can easily understand and see though the agent and the agent's recommendations. In so doing, consumers can be relieved from concerns related to information asymmetry that would hamper consumers' trust in the agent, as discussed in chapter 3. Sinha and Swearingen (2002)'s survey results indicate that users' high perceptions of agent transparency increase their confidence in the agents.

The transparency and user understanding of a medium are important to gain user trust in the medium (Lee and Turban, 2001). Based on observations from informal interviews and conversations with users of a variety of interactive systems, Nickerson (1999) and Hertzum et al. (2002) found that the transparency of a system facilitates users'

conceptualization of the systems, thus increases user trust in the system. Therefore, it is hypothesized that:

H6-7: Perceived agent transparency will positively influence consumer trust in online recommendation agents.

6.3.4 ROLE OF COGNITIVE EFFORT

The joint use of decision strategy support and explanation facilities is predicted to reduce agent restrictiveness while keeping high transparency levels. Nevertheless, the use of different features of an agent requires cognitive effort which is an important determinant of consumer behavior (e.g., Todd and Benbasat, 1992). According to the Production Paradox (Carroll and Rosson, 1987), end-users would like to accomplish as much work as possible and may not bother spending an extra effort learning about an agent or trying any advanced features. Based on the cognitive effort perspective (e.g., Todd and Benbasat, 1992), the conservation of effort is more important than increase in decision quality. Consumers' cognitive cost plays an important role in their use of agent functionalities, and in their evaluations and acceptance of the recommendation agents.

6.3.4.1 IMPACT OF DECISION STRATEGY SUPPORT AND EXPLANATION FACILITIES ON COGNITIVE EFFORT

Silver (1990) suggested that a DSS that presents many different features and options requires extra cognitive effort. Similarly, the functionalities supported by a Hybrid agent (i.e., selecting and switching between different decision strategies) will consume an extra effort. Beaulieu and Jones (1998) suggest that shifting the balance of control towards users requires the consumers to make deliberate decisions to exercise their control over choices, thus increasing their cognitive effort of using an agent. Therefore, it is posited that the consumers' cognitive effort will be higher in using the Hybrid agents, compared to the AC or EBA agents, which do not require users to choose from different strategies.

To estimate the levels of effort required to use the three types of agents, we conducted the Natural GOMS Language (NGOMSL) analyses devised by Kieras (1997). NGOMSL analyses are widely applied to predict the execution time of using a computer

system. The NGOMSL analyses show that prior to examining recommendations, Hybrid agents require about 15% longer execution time than the AC agents and about 41% longer execution time than the EBA agents, assuming all questions in the agent-user dialogues are answered by users and the agents are used only once (see appendix 6-2 for details).

Consumers also need to spend an effort in utilizing the explanation facilities. In the context of learning a word-processing system, Carroll and Kay (1985) found that excessive advice and explanations consumed a high amount of the user's cognitive effort. Todd and Benbasat (1992; 1994b; 1999; 2000) also noted the cognitive effort needed in understanding and using a decision aid with explanations. The use of explanations will thus increase the user's cognitive effort[23].

Frequently used objective measures for cognitive effort, after using an agent, is the consideration set size and decision time (Haubl and Trifts, 2000; Tan, 2003; Todd and Benbasat, 1992). A consideration set is defined as the set of alternatives that a consumer considers seriously before decision-making (Hauser and Wernerfelt, 1990). This is an indicator of the effort that a consumer spends in examining the recommendations from an agent. Häubl and Trifts (2000) found that the consideration set size is smaller when consumers use a recommendation agent. When explanations are provided, consumers can more easily judge the recommendations from an agent and will be more confident in the recommendations. Accordingly, users' consideration set size will be smaller and decision times shorter when explanation facilities are provided. Therefore, it is hypothesized that:

H6-8: The use of explanations reduces consumers' consideration size when using recommendation agents (H6-8a: Hybrid agents, H6-8b: AC agents, H6-8c: EBA agents).

H6-9: The use of explanations reduces consumers' decision time when using recommendation agents (H6-9a: Hybrid agents, H6-9b: AC agents, H6-9c: EBA agents).

In addition, when consumers utilize a Hybrid agent, which can better represent their decision strategy preferences, their consideration set size and decision time will be

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[23] The use of explanations was not considered in the NGOMSL analyses because it is difficult to estimate the time and effort involved in using the explanations, compared with other operators (e.g., moving the mouse).

reduced, since the recommendations would better reflect their preferences and they would be more confident in the agent's recommendations. Nevertheless, as previously stated, to get these benefits, consumers must first understand the agents and their capabilities. Only when explanations are provided, can the consideration set size become smaller and decision times shortened.

As mentioned earlier, while the EBA strategy eliminates product alternatives more easily than does the AC strategy, the EBA strategy may also eliminate good alternatives. The AC strategy may thus produce better recommendations. Although AC agents may provide more recommendations than the EBA agents, consumers' consideration set size as well as decision time will be similar in using these two agents. Therefore, we hypothesize:

H6-10a: With explanation use, the consideration set size of consumers using Hybrid agents will be smaller than that of consumers using AC agents or EBA agents; the consideration set size of consumers using AC agents will be similar to that of consumers using EBA agents.

H6-10b: Without explanations, the consideration set size of consumers using the Hybrid agents will be similar to that of consumers using AC agents or EBA agents.

H6-11a: With explanation use, the decision time of consumers using Hybrid agents will be less than that of consumers using AC agents or EBA agents; the decision time of consumers using AC agents will be similar to that of consumers using EBA agents.

H6-11b: Without explanations, the decision time of consumers using Hybrid agents will be similar to that of consumers using AC agents or EBA agents.

By considering both the savings in cognitive effort due to the smaller consideration set size, when explanations are provided in the Hybrid agents, and the extra cognitive effort needed to utilize the additional features provided by Hybrid agents, consumers' perceived overall cognitive effort should be the same for the three types of agents (Hybrid, AC, and EBA agents). Without explanations, however, consumers may still expend an effort in utilizing the additional features of a Hybrid agent, but cannot save any effort by reducing their consideration set size. Consequently, without

explanations, the consumers' perceived cognitive effort is greater with the Hybrid agents, compared to the AC or EBA agents.

In comparing the AC and EBA agents, the NGOMSL analyses show that AC agents require more effort in using the agents than EBA agents (see appendix 2). Still, the EBA agents may produce an empty set of recommendations due to the elimination strategy. Consumers thus may have to use the EBA several times to refine their preferences and arrive at the recommendations. As a result, the perceived cognitive effort in using these two agents will be similar. Therefore,

H6-12a: With explanation use, the perceived cognitive effort of consumers using Hybrid agents will be the same as that of consumers using AC agents or EBA agents.

H6-12b: Without explanations, the perceived cognitive effort of consumers using Hybrid agents will be greater than that of consumers using AC or EBA agents; the perceived cognitive effort of consumers using AC agents will similar to that of consumers using EBA agents.

Similarly, although the use of explanations requires cognitive effort, considering both the cognitive effort in using the explanations and the reduced effort in examining fewer recommendations, use of explanations should not influence consumers' perceived cognitive effort. Therefore,

H6-13: Use of explanations will not influence consumers' perceived cognitive effort in using recommendation agents (H6-13a: Hybrid agents, H6-13b: AC agents, H6-13c: EBA agents).

6.3.4.2 IMPACT OF COGNITIVE EFFORT ON PERCEIVED EASE-OF-USE OF AGENTS

The major impact of perceived cognitive effort is on the perceived ease-of-use (PEOU) of an agent, which is determined in part by how much effort consumers must spend in using the recommendation agents (Davis, 1989; Gefen et al., 2003b). Therefore, it is hypothesized:

H6-14: Perceived cognitive effort (H6-14a), consideration size set (H6-14b), and decision time (H6-14c) will negatively influence consumers' PEOU of recommendation agents.

6.3.5 TRUST-TAM

The left part of the research model (see figure 6-2) examines the impact of decision strategy support and explanation facilities on perceived agent restrictiveness, perceived agent transparency, consideration set size, decision time, and perceived cognitive effort, as well as the effects of these variables on the antecedents in Trust-TAM (i.e., trust, PU, and PEOU). This section lists the hypotheses on the right side of the research model which replicates the model investigated in chapter 4.

H6-15: PU of recommendation agents will positively affect consumers' intentions to adopt the agents.

H6-16: PEOU of recommendation agents will positively affect consumers' intentions to adopt the agents.

H6-17: PEOU of recommendation agents will positively affect PU of the agents.

H6-18: Trust in recommendation agents will positively affect consumers' intentions to adopt the agents.

H6-19: Trust in the recommendation agents will positively affect PU of the agents.

H6-20: PEOU of recommendation agents will positively affect consumers' trust in the agents.

6.4 Research Method

A laboratory experiment was conducted to test the hypotheses listed in section 6.3. Section 6.4.1 describes the experimental design and treatments. Control variables are introduced in section 6.4.2, and the dependent variables and development of several new

measures are introduced in sections 6.4.3 and 6.4.4. Section 6.4.5 describes the participants and section 6.4.6 presents the experimental procedures.

6.4.1 INDEPENDENT VARIABLES AND EXPERIMENTAL DESIGN

The two main independent variables are 1) decision strategy support (as implemented in the three types of agents with different levels: Hybrid, AC, and EBA agents), and 2) use of explanations. The experimental agent in Experiment 1 was expanded to incorporate the experimental treatments for this experiment. Some questions in the agent-user dialogue were updated based on comments from the pilot tests for this study and from digital camera experts. In total, there were 11 questions in the agent-user dialogue. The product database was also updated to include digital camera models that were available on the market at the time of the experiment.

A three (agent types: Hybrid agents, AC agents, and EBA agents) × two (explanations: With and Without) between-subject factorial design (see table 6-1) was used. This design allows for the determination of relative impact of different agents with different decision strategy support levels and explanation facilities, individually and in interactions with each other.

Table 6-1 3 × 2 Full Factorial Experimental Design				
		Types of Agent (Different Decision Strategy Support)		
		Hybrid Agent	AC Agent	EBA Agent
Explanations	With	Group 1	Group 2	Group 3
	Without	Group 4	Group 5	Group 6

Explanation facilities were studied in Chapter 3. Three types of explanations (i.e., *how* explanations, *why* explanations, and *guidance*) were found to be effective in enhancing trust in online recommendation agents. These three types of explanations were also used in this study, but the content of explanations was adjusted according to the agent decision strategy changes. Similar to the agent in Experiment 1, explanations were also provided for each of the final recommendations. In addition to the three types of explanations for each question in the agent-user dialogues, *guidance* for choosing different strategies is provided for the Hybrid agents with explanations.

In an effort to assess the face validity and definitional accuracy of the updated explanations that were incorporated into the agent prototype, a pilot test similar to the one in Experiment 1 was conducted. Eight graduate students majoring in Management Information Systems (MIS) were asked to classify the explanations to be examined in this study into one of the three types (i.e., *how* explanations, *why* explanations, and *guidance*) or none of them. In addition, to get the certainty levels of their judgment, participants were asked to indicate on a five-point scale, to what extent the explanation fits well with the definition of the type of explanation chosen. A validation example is provided in figure 6-3.

Please read the explanation carefully, identify what type of explanation it belongs, and provide your comments on the explanation (regarding the **grammar structure, vocabulary,** *etc).*

Refer to question No. 3   **Exp. No. 3**

The purpose of asking this question is to know what kinds of photos you will take most often. It is quite useful to take photos at different distances. For example, for portraits of family and friends, subjects are close to your camera, but for many scenery or artistic photos, subjects may be far from your camera.

• According to the definitions of three explanation types, please check the type it belongs to:

How explanation ☐	*Why* explanation ☐	*Guidance* ☐	None ☐

If you did not choose "none", please indicate the extent to which you agree with the statement: "This explanation fits well with the definition of the type of explanation I chose"

1	2	3	4	5
☐	☐	☐	☐	☐
Not sure/guess		*A bit Sure*		*Very Sure*

The validation results are reported in table 6-2. Most of the explanations were correctly classified. The certainty levels were high (average scores on a five-point scale: 4.6, 4.3, 4.7 for *how* explanations, *why* explanations, and *guidance*, respectively). The explanations thus appeared to be consistent with their definitions. The suggestions that were made during the pilot test regarding clarity in wording were incorporated into the explanations used for the main experiment.

Table 6-2 Explanation Validation Results			
	How explanations	*Why* explanations	*Guidance*
How explanations	**96.6%**	0.0%	2.3%
Why explanations	0.0%	**81.8%**	2.3%
Guidance	3.4%	18.2%	**95.5%**
None	0.0%	0.0%	0.0%
Total	*100%*	*100%*	*100%*

Table 6-3 provides examples of the finalized *how* explanations, *why* explanations, and *guidance* for a question in the agent-user dialogue. The *guidance* for the strategy choice for all questions is as follows:

I will use different approaches to make recommendations based on your choice of "non-essential" or "essential" preference. If you want me to recommend only those cameras that exactly satisfy your desired choice to this question, please select the "essential preference." On the contrary, if you want me to recommend all cameras that fit your overall preferences quite well but might not exactly satisfy your desired choice to this question, please select the "non-essential preference."

Please be advised that choosing "essential preference" or very high importance levels in the "non-essential preference" will significantly reduce the number of recommendations that I could provide."

Table 6-3 Examples of *how* explanations, *why* explanations, and *guidance*	
A Question in the Agent-User Dialogue	How far will you be from most of the subjects that you photograph? 1). Immediate vicinity 2). A moderate distance or less 3). Far away, in addition to immediate and moderate vicinity
How Explanation	Your distance from the subjects you want to focus on most often will determine the suitable zoom level of a digital camera. If you choose "non-essential preference", cameras with your desired optical zoom level will be given higher priority in my recommendations; if you choose "essential preference", I will only recommend cameras with your desired optical zoom level. Specifically, the four options will determine the following zoom levels: 1) 2X optical zoom and below. 2) Between 2X and 5X optical zoom. 3) 4X optical zoom and above.
Why Explanation	The purpose for asking this question is to know what kinds of photos you will take most often. It is quite useful to take photos at different distances. For example, for portraits of family and friends, your subjects may be close to your camera, but for many scenery or artistic photos, the subjects may be far from your camera.
Guidance	Most digital cameras can take pictures beyond the immediate vicinity. However, cameras capable of taking pictures from very far away will be more expensive. As well, your choices will be more limited (only about 20% of cameras can focus on distant objects). Hence, be careful not to over-estimate your needs.

Appendix 6-1 provides screenshots of agent interfaces in different experimental conditions. A sample question in the agent-user dialogue of the Hybrid agent with explanations is presented in figure A6-1(a). When the "non-essential preference" button (i.e., AC strategy) was clicked, participants were prompted to indicate an importance weight (figure A6-1(b)). Alternatively, participants could choose the "essential preference," indicating an EBA strategy (figure A6-1(c)).

For the agents in the "with" explanation conditions, three buttons (i.e., a "How" button for *how* explanations, a "Why" button for *why* explanations, and a "Guidance"

button for *guidance*) were provided for each question in the agent-user dialogue[24]. When one of the buttons is clicked, the corresponding explanation is shown in the area below the "Explanation / Guidance" icon (figure A6-1(d) in appendix 6-1). For the Hybrid agent with explanations, underneath the choice of "non-essential preference" or "essential preference," a button with the text of "Guidance on Non-Essential vs. Essential" is provided. Clicking the button shows the content of the *guidance* for choosing different strategies (figure A6-1(e)).

The sample question pages for the AC and EBA agents are shown in figure A6-1(f) and A6-1(g), respectively. The final recommendation pages for the Hybrid and AC agents with a fit score for each recommended product are shown in figure A6-1(h). Figure A6-1(i) shows the interface when an explanation for a recommendation is clicked and presented. For the EBA agents, the final recommendation page is shown in figure A6-1(j) which does not have fit scores for the recommendations. For the "without" explanation conditions, the interfaces are similar to the corresponding "with" explanation conditions, except for the "How", "Why", "Guidance", and "Guidance on Non-Essential vs. Essential" buttons which are not provided.

6.4.2 CONTROL VARIABLES

All control variables used in Experiment 1 were captured again, including: consumers' trust propensity, product expertise, and preferences for effort-saving vs. decision quality. In addition, another control variable – product involvement – was included. Product involvement was defined as a person's motivational state (i.e., arousal, interest, drive) towards an object based on the relevance or importance of a product class (Koufaris, 2002; Zaichkowsky, 1985; 1994). Product involvement has been shown to influence various consumer behaviors, including search behavior, information processing, and extensiveness of decision-making process (e.g., Celsi and Olson, 1988; Dholakia, 2001). A consumer, who is very involved in a product, is likely to spend more time and effort in deciding what to buy. On the other hand, a consumer, who does not consider a purchase decision to be important and is only marginally involved in the product, will make the

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[24] Note that this is different from Experiment 1 where the three types of explanations were manipulated in a 2 × 2 × 2 factorial design.

choice without much deliberation or cognitive effort. Therefore, product involvement is expected to influence consumers' willingness to spend effort, and the extent to which they use the agent and its embedded features. As a result, the effectiveness of the agent will be influenced.

6.4.3 DEPENDENT VARIABLES

Among the various dependent variables investigated in this study, PU, PEOU, trust, intentions to adopt recommendation agents, and perceived cognitive effort have well-established multi-item measures in the literature. Measures for PU and PEOU were adapted from Koufaris (2002) and Davis (1989). Measures for intentions to adopt recommendation agents, perceived cognitive effort, and trusting beliefs were adapted from Venkatesh (2000; 2003), Pereira (2000), and McKnight et al. (2002a), respectively.

Two variables − consideration set size and decision time − used objective measures. Similar to prior studies (e.g., Haubl and Trifts, 2000; Tan, 2003), consideration set size was operationalized as the number of products that were examined by clicking the detailed product information links before participants made their choice. Participants' navigation screens during the experiment were recorded unobtrusively as videos by screen capture software (Camtasia Recorder 3.0). The numbers of products that were examined by participants were counted by reviewing the recorded videos. The times spent by participants in the experimental tasks (decision times) were recorded on experimental minutes sheets by the research assistant for the experiment.

Based on Moore and Benbasat (1991), new measures were developed for two dependent variables: 1) perceived agent restrictiveness (perceived strategy restrictiveness, in particular) and 2) perceived agent transparency. Silver (1988) investigated how the users of different types of DSS differ in their perceptions of system restrictiveness. Nevertheless, Silver did not directly measure user perceptions of restrictiveness, but asked participants to provide the relative positions of different DSS by ranking their perceptions of restrictiveness for these systems. Given the between-subject design used in this experiment, Silver's approach was not applicable, and new measures were developed. The development process and results are reported in section 6.4.4.

Perceived agent transparency was measured by Sinha and Swearingen (2002) using a single item – *"Do you understand why the system recommended this item to you?"* Since it is difficult to verify the reliability and validity of a variable measured by a single item, multi-item measures were developed in this study.

For control variables, the trust propensity measures were adapted from McKnight (2002a). Four sub-constructs were included in the trust propensity construct: 1) competence, 2) benevolence, 3) integrity, and 4) trusting stance. For product involvement, the enduring product involvement for the product category of digital camera was measured. Zaichkowsky's (1985; 1994) simplified 10-item measure was used. This measure is widely applied in consumer behavior studies. Measures for participant preferences for effort-saving vs. decision quality were adapted from Komiak (2003). Participants' product knowledge was measured in both subjective and objective ways. Flynn and Goldsmith (1999)'s subjective measures for product knowledge were used and the objective measures were based on those of Komiak (2003).

The measurement items for all dependent and control variables are provided in appendix 6-3.

6.4.4 MEASUREMENT DEVELOPMENT

In an effort to develop measures for perceived strategy restrictiveness and perceived agent transparency, we followed the approach developed by Moore and Benbasat (1991). The starting point for the scale development was the previous empirical and theoretical literature. We could not find well-developed measures, however, and began to generate a sample of measurement items by recruiting four participants (two graduate students: one from the Department of Psychology and the other from the Faculty of Science, and two assistant professors in MIS). The subjects were provided with definitions of the two constructs from prior studies and dictionaries, and asked to suggest measurement items. Then, to further check content validity, the instrument was submitted to a panel of graduate students majoring in MIS to obtain their views on which items were appropriate to include. This procedure finally generated seven items for perceived strategy restrictiveness and another seven items for perceived agent transparency.

A card sorting exercise (Moore and Benbasat, 1991) was next used in the scale development process. Each item was printed on a 3 × 5-inch index card. The three trusting belief measures that were validated in McKnight et al. (2002a) were adapted and shuffled into a random order, together with the newly created measures for presentation to the judges. Two rounds of this exercise were conducted. In the first round, four master's and doctoral students were asked to sort the items into separate categories, based on the similarity and differences of the items, and then label the underlying constructs for each of their categories. The average inter-judge raw agreement rate was 73%. The judges also provided comments on ambiguous or unclear items. In this process, only one item of perceived strategy restrictiveness was identified as being too ambiguous. All other items were refined according to the judges' comments and retained for the next sorting round.

In the second round, another four master's and doctoral students were asked to sort the refined and retained items based on construct definitions. A "too ambiguous/doesn't fit" category was also included so that the judges did not force to fit any item into a particular predefined category. This round of sorting ended with an

average raw agreement rate of 95%, indicating a very high reliability (Moore and Benbasat, 1991). This process also helped establish the discriminant validity of the items. The resulting measures for perceived strategy restrictiveness and perceived agent transparency contained six and seven items (appendix 6-3), respectively. These measures were further validated in the main experiment and the validation results are reported in section 6.5.3.

6.4.5 PARTICIPANTS

Participants in this experiment were recruited campus-wide from the University of British Columbia. The majority were university students. The sample size is determined by the estimated effect size, intended significance level and statistical power. As in most behavioral studies, we chose 0.05 as the significance level and 0.8 as the level of statistical power (Cohen, 1988). Based on the effect sizes from Experiment 1, the effect size of the impact of explanation use on trust is assumed to be around medium. To our knowledge, no prior studies have empirically studied the impact of decision strategy support and the interaction between explanation use and decision strategy support, thus a medium effect size was assumed (Cohen, 1988, p. 390). Based on these criteria, 26 participants per cell (156 participants in total) were needed for this study.

To reduce potential evaluation bias, we planned to screen out those experimental volunteers who own or have purchased digital cameras before, as we had done in Experiment 1. Nevertheless, we found that many student volunteers had digital cameras, hence it would be difficult to recruit a sufficient number of participants if they were screened out. Rather, in the online form to sign up for the experiment, an additional question was asked to elicit their expertise levels: *"How much do you know about digital cameras?"*[25] A seven-point scale was used, ranging from "Not at all" (1) to "Expert" (7). In addition to the volunteers who did not own or had not purchased a digital camera before, we invited those having levels of expertise below 4 on a 7-point scale. Given that our experimental agent platform has a limited number of cameras in its database, this screening process helps reduce the influence of this limitation on participants'

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[25] This measure was employed to screen out subjects. It differs from the product expertise, which was used as a control variable in the experiment and was measured by multi-items (appendix 6-3).

evaluations of the agent. In addition, this screening process is valid in that those who own or purchased digital cameras and have high expertise in digital cameras may not need advice on what to buy and do not belong to the population of our interest.

6.4.6 EXPERIMENTAL TASKS AND PROCEDURES

Similar shopping tasks as used in Experiment 1 were used in this study. Participants were asked to finish two tasks. One was to choose a digital camera for a good friend as a wedding gift and the cost would be shared with another four friends. The other was to select a digital camera for a close family member. Participants were informed that the tasks are flexible and they may make as many assumptions as they wish.

All participants were randomly assigned to one of the treatment groups. Each participant was guaranteed a monetary compensation ($15) for participating. To motivate participants to view the experiment as a serious online shopping session and to increase their involvement, participants were informed before the experimental tasks that 25% of the participants could get an additional award from $5 to $100 based on their performance. They were also informed that they would be asked to provide their justifications for their shopping choices and that their performance will be judged based on how convincing their justifications are in supporting their shopping choices.

The experimental procedures were the same as those in Experiment 1. A research assistant first trained participants on how to use and navigate the assigned Web interface using recorded videos that showed a tutorial agent with the same features as the experimental agent for that condition. Then, each participant was asked to finish the above two tasks. The order of the two tasks was counter-balanced. After each task, participants were directed to an online form to write down their choice and their justifications for the choice. The tasks had no time limit. Finally, after performing the two tasks, participants were asked to complete a questionnaire that included the measures of dependent variables.

6.5 Data Analysis and Results

This section begins by reporting demographic data about participants in the experiment. Manipulation check results are reported in section 6.5.2. A multiple analysis of covariance (MANCOVA) was conducted as the starting point to test whether or not the experimental treatments have an overall direct impact on the dependent variables (i.e., perceived strategy restrictiveness, perceived agent transparency, perceived cognitive effort, decision time, and consideration set size) (Hair et al., 1998), with a follow-up analysis of covariance (ANCOVA) performed on individual variables (section 6.5.4).

A Partial Least Squares (PLS) analysis, as implemented in PLS-Graph 3.00 (Chin, 2001), was used to assess the measurement properties of the dependent variables and the structural model.[26] The measurement properties of the dependent variables are presented in section 6.5.3 and the results of the structural model are reported in section 6.5.5. PLS was chosen over LISREL for two main reasons (Barclay et al., 1995). First, to our knowledge, this is the first study to test the role of perceived strategy restrictiveness and perceived agent transparency in building consumers' trust in agents, thus the focus is on theory-development rather than theory-testing. Second, the sample size (N=156) is enough for the PLS analysis, while a larger sample size is needed for the LISREL, given the complexity of our structural model and many paths that must be estimated.

6.5.1 DEMOGRAPHIC DATA

Table 6-4 outlines the characteristics of the participants who volunteered in the experiment. The majority were undergraduate students, and their ages were generally around 20 years, which matches the Internet user demographic data (Johnson, 2005). Overall, most participants were experienced Internet users. About two-thirds were female and one-third were male.

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[26] Conducting group comparisons in PLS is difficult. Given the three types of agents, group comparisons are needed. Therefore, in addition to PLS structural model testing, we also conducted ANCOVA, to test the direct impact of decision strategy support and explanation use as well as their interaction effects on perceived strategy restrictiveness, perceived agent transparency, consideration set size, decision time, and perceived cognitive effort. The Scheffe multiple comparisons were performed in an ANOVA.

Table 6-4 Demographic Data		
	# of Participants	Percentage
Gender		
Male	106	67.9%
Female	50	32.1%
Age		
18~20	91	58.3%
21~25	54	34.6%
26~30	5	3.2%
31~35	4	2.6%
36~40	0	0
41 and above	2	1.3%
Internet Use Experience		
Less than 1 year	1	0.6%
Between 1 and 3 years	3	1.9%
Between 3 and 6 years	68	43.6%
Longer than 6 years	84	53.8%
Year in School		
Freshman	31	19.9%
Sophomore	50	32.1%
Junior	34	21.8%
Senior	29	18.6%
Graduate	5	3.2%
Other	7	4.5%
Internet Usage		
Less than 30 minutes per day	3	1.9%
Between 30 minutes and 1 hours per day	36	23.1%
Between 1 and 2 hours per day	39	25.0%
More than 2 hours per day	78	50.0%

In the background questionnaire, participants were asked about their attitudes towards computers and web-shopping risk. Their comfort levels with the Internet and online shopping were also assessed. No significant differences were found between subjects randomly assigned to one of the experimental groups for each of these variables. Also, no significant differences were found between groups with respect to participants' age, gender, Internet usage, and Internet experience.

6.5.2 MANIPULATION CHECKS

Manipulation checks were conducted for the two experimental treatments. To utilize the decision strategy in the Hybrid agents, participants were required to choose either "non-

essential preference" (i.e., AC strategy) or "essential preference" (i.e., EBA strategy) for each question, after deciding to reply to that question. Participants were given a reminder message in the "explanations/guidance" window if they forgot to make the choice. If the "non-essential preference" was chosen, participants were required to indicate an importance weight, and a reminder message was also given if they forgot to choose an importance weight. Table 6-5 reports the distribution of strategy choices by participants in the two Hybrid agent conditions (i.e., one "with" explanations and the other "without" explanations). Because participants were allowed to change and refine their choices, the distributions of strategy choice that are based on initial choices and final choices are summarized separately. On average, about 40% of participants' choices were "essential preference," while the remaining choices were for "non-essential." The results show that most subjects utilized both the EBA strategy and the AC strategy, indicating that a Hybrid strategy was employed. Therefore, our implementation of the Hybrid agents is considered to be successful.

Table 6-5 Distribution of Strategy Choice for the Hybrid Agents				
% of "Essential Preference" chosen (% of "Non-essential Preference" chosen)	# of participants using the Hybrid agent in the "with" explanation group (%)		# of participants using the Hybrid agent in the "without" explanation group (%)	
	Based on *Initial* Choice	Based on *Final* Choice	Based on *Initial* Choice	Based on *Final* Choice
100% (0%)	2 (7.6%)	2 (7.6%)	1 (3.8%)	0 (0%)
75.0% - 99.9% (0.1% - 25.0%)	0 (0%)	0 (0%)	1 (3.8%)	1 (3.8%)
50.0% - 74.9% (25.1% - 50.0%)	6 (23.1%)	5 (19.2%)	8 (30.8%)	9 (34.6%)
25.0% - 49.9% (50.1% - 75.0%)	10 (38.5%)	8 (30.8%)	11 (42.3%)	11 (42.3%)
0.1% - 24.9% (75.1% - 99.9%)	5 (19.2%)	8 (30.8%)	4 (15.4%)	4 (15.4%)
0% (100%)	3 (11.5%)	3 (11.5%)	1 (3.8%)	1 (3.8%)
Average % of "Essential Preference" chosen	*40.1%*	*35.7%*	*42.1%*	*40.8%*
Average % of "Non-Essential Preference" chosen	*59.9%*	*64.3%*	*57.9%*	*59.2%*

For the AC agents, participants were required to indicate an importance weight after deciding to reply to a question, and were reminded if they forgot to make their indication. The strategy was then executed by the agent. For EBA agents, after participants answered the questions in the agent-user dialogue, the EBA strategy was executed by the agents.

Explanation use was counted by watching over the videos recorded in the experiment. Similar counting procedures were applied as those in Experiment 1. On average, 31% of the *how* explanations, 22% of the *why* explanations, and 25% of the *guidance* were viewed by participants. The average usage rates are similar to those in

other empirical studies (e.g., Dhaliwal, 1993). But the rates are lower than those in Experiment 1. One possible reason is that in Experiment 1, many participants in the "with" explanation conditions were provided by only one or two types of explanations while in this experiments, all participants in the "with" explanation conditions were provided with all three types of explanations. When all three types of explanations were provided, consumers might be more selective in choosing explanations to view, thus the usage rates are lower. The detailed frequency distributions of explanation use are reported in table 6-6. Overall, the three types of explanations in the experimental agents were extensively used and the experimental manipulations are quite successful.

Table 6-6 Frequency Distributions of Explanation Use					
How explanations		*Why* explanations		*Guidance*	
% of *how* explanations used (pc)	Number of subjects	% of *why* explanations used (pc)	Number of subjects	% of *guidance* used (pc)	Number of subjects
pc = 0[a]	5	pc = 0	5	pc = 0	9
0 <pc≤ 10%	17	0 <pc≤ 10%	25	0 <pc≤ 10%	26
10% <pc≤ 30%	21	10% <pc≤ 30%	20	10% <pc≤ 30%	12
30% <pc≤ 50%	19	30% <pc≤ 50%	16	30% <pc≤ 50%	16
50% <pc≤ 70%	13	50% <pc≤ 70%	4	50% <pc≤ 70%	4
pc > 70%	2	pc > 70%	2	pc > 70%	5
Total	72[b]	Total	72	Total	72

[a] There are some participants who did not view any explanations for a particular type of explanations and two participants did not view any explanations for all three types of explanations. Dropping these two participants did not change the hypothesis testing results. Therefore, in the current analysis, all participants were retained.

[b] In total, 78 participants were assigned to the conditions of "with" explanations. But for 6 of them, their navigations and screens were not successfully recorded. Therefore, only 72 participants' explanation use rates were analyzed.

6.5.3 MEASUREMENT MODEL

All dependent variables, except for the three objective measures (i.e., consideration set size, decision time, and recommendation adoption) were modeled as reflective constructs. The descriptive data about the dependent variables are shown in table 6-7. Following

Barclay et al. (1995)'s approach to test measurement models in PLS, we examined: 1) individual item reliability; 2) internal consistency; and 3) discriminant validity. Individual reliability is examined by the loadings of measures with their corresponding construct (table 6-7). Most of the loadings exceed 0.7, complying with a common rule of thumb that indicates good item reliability. The loadings of some items for perceived strategy restrictiveness and perceived agent transparency were between 0.56 and 0.70. As suggested by Barclay at el. (1995), this is not uncommon for newly developed measures and should keep as many items as possible unless there are significant deviations in the items. Further examination of these items revealed that they have good content validity and their loadings are not very low, so that all items were retained at this stage.

Table 6-7 Means (Standard Deviations) of Dependent Variables							
Explanations	Agent Type	Perceived Strategy Restrictiveness (PSR)	Perceived Agent Transparency (PAT)	Perceived Cognitive Effort (PCE)	Competence belief in agents (CMPT)	Benevolence belief in agents (BNVL)	Integrity belief in agents (INTG)
With	Hybrid	3.62 (1.09)	5.25 (0.95)	2.71 (1.21)	4.80 (1.22)	4.60 (1.03)	5.02 (0.84)
	AC	3.79 (0.90)	5.22 (0.98)	2.47 (1.02)	4.99 (0.78)	4.60 (0.96)	4.76 (0.81)
	EBA	4.69 (0.89)	5.08 (0.99)	3.45 (1.21)	3.57 (1.48)	4.10 (1.37)	4.88 (1.06)
	Total	*4.03 (1.06)*	*5.18 (0.96)*	*2.84 (1.20)*	*4.45 (1.34)*	*4.44 (1.15)*	*4.89 (0.90)*
Without	Hybrid	4.29 (1.04)	3.87 (1.34)	3.31 (1.29)	3.87 (1.54)	3.67 (1.07)	4.20 (0.93)
	AC	3.98 (0.90)	4.49 (0.81)	2.39 (0.94)	4.64 (0.98)	4.17 (1.10)	4.55 (0.77)
	EBA	4.38 (0.82)	4.38 (1.30)	3.15 (1.37)	3.62 (1.63)	3.77 (1.19)	4.39 (0.71)
	Total	*4.22 (0.93)*	*4.25 (1.20)*	*2.95 (1.27)*	*4.04 (1.46)*	*3.87 (1.13)*	*4.38 (0.81)*
Total	Hybrid	3.95 (1.11)	4.56 (1.35)	3.01 (1.28)	4.33 (1.46)	4.14 (1.14)	4.61 (0.97)
	AC	3.88 (0.90)	4.86 (0.96)	2.43 (0.97)	4.81 (0.89)	4.39 (1.05)	4.65 (0.79)
	EBA	4.54 (0.86)	4.73 (1.20)	3.25 (1.29)	3.59 (1.54)	3.94 (1.28)	4.63 (0.93)
	Total	*4.12 (1.00)*	*4.72 (1.18)*	*2.90 (1.23)*	*4.25 (1.41)*	*4.15 (1.17)*	*4.63 (0.89)*

Table 6-7 Means (Standard Deviations) of Dependent Variables (cont'd)						
Explanations	Agent Type	PU of Agents (PU)	PEOU of Agents (PEOU)	Intentions to Adopt Agents (INTN)	Consideration Set Size[a] (SIZE)	Decision Time[a, b] (TIME)	Recommendation Adoption[a] (RCMA)
With	Hybrid	4.99 (1.45)	5.59 (0.77)	4.59 (1.76)	9.20 (7.10)	35.81 (14.72)	1.71 (0.57)
	AC	5.23 (0.98)	5.79 (0.76)	4.56 (1.47)	17.23 (15.09)	38.38 (14.88)	1.69 (0.43)
	EBA	4.29 (1.44)	5.28 (1.01)	3.64 (2.04)	14.60 (10.81)	32.19 (10.00)	1.02 (0.71)
	Total	4.84 (1.35)	5.56 (0.87)	4.26 (1.80)	13.72 (11.86)	35.46 (13.47)	1.48 (0.66)
Without	Hybrid	4.34 (1.65)	5.35 (1.26)	3.78 (1.82)	17.42 (21.77)	32.38 (12.78)	1.44 (0.75)
	AC	5.00 (0.84)	5.38 (0.92)	4.69 (1.60)	16.58 (9.72)	35.58 (17.42)	1.40 (0.58)
	EBA	4.12 (1.50)	5.02 (1.08)	3.51 (1.69)	15.29 (19.01)	28.81 (14.35)	1.23 (0.81)
	Total	4.49 (1.41)	5.25 (1.09)	4.00 (1.76)	16.46 (13.35)	32.26 (15.04)	1.36 (0.71)
Total	Hybrid	4.67 (1.57)	5.47 (1.04)	4.19 (1.82)	13.39 (16.69)	34.10 (13.76)	1.58 (0.67)
	AC	5.11 (0.91)	5.59 (0.86)	4.63 (1.52)	16.90 (12.57)	36.98 (16.11)	1.55 (0.53)
	EBA	4.21 (1.46)	5.15 (1.05)	3.58 (1.85)	14.94 (15.22)	30.50 (12.37)	1.12 (0.76)
	Total	4.66 (1.39)	5.41 (1.00)	4.13 (1.78)	15.09 (14.88)	33.86 (14.32)	1.42 (0.68)

[a] These three are objective measures.

[b] The measurement unit of decision time is minute.

Internal consistency was examined by the composite reliability developed by Fornell and Larcker (1981), as a measure of reliability similar to Cronbach's alpha. Both composite reliability and Cronbach's alpha are reported in table 6-8. The benchmark for acceptable reliability is 0.7. All constructs met this criterion, indicating that the measures have good internal consistency.

In PLS, discriminant validity can be examined by two criteria. One criterion is that a construct should share more variance with its own measures than it shares with other constructs in a model. The measure of Average Variance Extracted (AVE),

suggested by Fornell and Larcker (1981), was used and the square root of AVE of a construct should be greater than the correlations between the construct with other constructs (Barclay et al., 1995). Table 6-8 shows the square roots of AVEs and correlations between constructs. The results met this criterion.

A second criterion for discriminant validity is that no item should load more highly with a construct other than the construct it intends to measure. The loadings and cross-loadings of measures are shown in table 6-9. An examination of the matrix reveals that all items except for one item for perceived cognitive effort (PCE2) satisfied this criterion. Therefore, PCE2 was dropped from the further analysis and all others items were retained.

Table 6-8 Internal Consistencies, AVEs, and Correlations of Constructs

	Alpha	Internal Consistency	1	2	3	4	5	6	7	8	9	10	11	12
1. Perceived Strategy Restrictiveness	0.73	0.82	0.66[b]											
2. Perceived Agent Transparency	0.92	0.93	-0.36**	0.80										
3. Perceived Cognitive Effort	0.91	0.91	0.51**	-0.58**	0.79									
4. Competence belief in agents	0.91	0.95	-0.52**	0.56**	-0.73**	0.91								
5. Benevolence belief in agents	0.72	0.88	-0.40**	0.54**	-0.71**	0.67**	0.81							
6. Integrity belief in agents	0.82	0.93	-0.59**	0.59**	-0.73**	0.81**	0.57**	0.88						
7. PU of Agents	0.94	0.84	-0.44**	0.52**	-0.52**	0.64**	0.50**	0.70**	0.80					
8. PEOU of Agents	0.84	0.87	-0.21**	0.59**	-0.38**	0.46**	0.45**	0.47**	0.61**	0.79				
9. Intentions to Adopt Agents	0.97	0.99	-0.54**	0.49**	-0.64**	0.84**	0.55**	0.76**	0.58**	0.43**	0.98			
10. Consideration Set Size[a]	--	--	0.21**	-0.43**	0.41**	-0.39**	-0.29**	-0.41**	-0.32**	-0.26**	-0.35**	--		
11. Decision Time[a]	--	--	0.00	-0.16	0.21**	-0.14	-0.08	-0.09	-0.15	-0.04	-0.09	0.51**	--	
12. Recommendation Adoption[a]	--	--	-0.32**	0.36**	-0.40**	0.42**	0.33**	0.49**	0.19*	0.15	0.33**	-0.51**	-0.17*	--

[a] These three constructs are objective measures and each has only one item.

[b] The scores in the diagonal of the matrix are square roots of AVEs while the lower triangle represents the correlations between constructs.

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 6-9 Loading and Cross-Loadings of Measures

	PSR	PAT	PCE	PU	PEOU	CMPT	BNVL	INTG	INTN	SIZE	TIME	RCMA
PSR1	**0.592**	-0.285	0.393	-0.317	-0.306	-0.346	-0.204	-0.185	-0.367	0.159	-0.023	-0.252
PSR2	**0.719**	-0.221	0.394	-0.397	-0.326	-0.390	-0.352	-0.031	-0.427	0.177	0.072	-0.159
PSR3	**0.758**	-0.398	0.391	-0.468	-0.345	-0.466	-0.393	-0.307	-0.435	0.317	0.144	-0.259
PSR4	**0.560**	-0.114	0.271	-0.216	-0.167	-0.289	-0.206	-0.063	-0.243	-0.042	-0.124	-0.161
PSR5	**0.623**	-0.111	0.248	-0.254	-0.175	-0.348	-0.158	-0.054	-0.253	0.000	-0.083	-0.244
PSR6	**0.691**	-0.211	0.304	-0.340	-0.227	-0.447	-0.341	-0.115	-0.366	0.101	-0.061	-0.199
PAT1	-0.333	**0.759**	-0.445	0.427	0.333	0.512	0.452	0.389	0.434	-0.340	-0.060	0.254
PAT2	-0.265	**0.805**	-0.418	0.407	0.441	0.378	0.384	0.449	0.316	-0.273	-0.108	0.171
PAT3	-0.238	**0.592**	-0.413	0.317	0.356	0.312	0.188	0.302	0.274	-0.340	-0.144	0.240
PAT4	-0.331	**0.880**	-0.561	0.553	0.561	0.578	0.547	0.547	0.467	-0.369	-0.121	0.340
PAT5	-0.249	**0.860**	-0.448	0.439	0.400	0.418	0.398	0.508	0.376	-0.346	-0.186	0.309
PAT6	-0.256	**0.845**	-0.505	0.518	0.490	0.552	0.451	0.523	0.423	-0.412	-0.161	0.364
PAT7	-0.329	**0.837**	-0.476	0.445	0.443	0.482	0.422	0.533	0.431	-0.367	-0.113	0.335
PCE1	0.554	-0.502	**0.809**	-0.635	-0.538	-0.736	-0.468	-0.339	-0.634	0.402	0.137	-0.349
PCE2	0.464	-0.525	**0.757**	-0.748	-0.575	<u>-0.782</u>	-0.593	-0.411	-0.678	0.388	0.113	-0.494
PCE3	0.252	-0.337	**0.744**	-0.447	-0.480	-0.399	-0.235	-0.161	-0.354	0.214	0.188	-0.233
PCE4	0.420	-0.479	**0.803**	-0.641	-0.606	-0.598	-0.446	-0.264	-0.542	0.493	0.212	-0.425
PCE5	0.422	-0.451	**0.888**	-0.570	-0.611	-0.536	-0.353	-0.291	-0.454	0.238	0.216	-0.246
PCE6	0.249	-0.433	**0.699**	-0.348	-0.520	-0.314	-0.302	-0.283	-0.281	0.144	0.139	-0.087
PU1	-0.415	0.487	-0.593	**0.900**	0.632	0.657	0.550	0.436	0.728	-0.301	-0.064	0.327
PU2	-0.500	0.502	-0.673	**0.922**	0.645	0.733	0.550	0.410	0.790	-0.362	-0.161	0.359
PU3	-0.477	0.492	-0.631	**0.914**	0.586	0.702	0.632	0.395	0.736	-0.371	-0.196	0.349
PU4	-0.488	0.556	-0.747	**0.896**	0.565	0.847	0.600	0.427	0.783	-0.399	-0.096	0.495
PEOU1	-0.266	0.345	-0.508	0.423	**0.777**	0.345	0.314	0.378	0.394	-0.089	0.014	0.184
PEOU2	-0.334	0.567	-0.562	0.536	**0.808**	0.525	0.441	0.405	0.434	-0.386	-0.085	0.319
PEOU3	-0.342	0.394	-0.555	0.663	**0.806**	0.533	0.454	0.373	0.548	-0.244	-0.079	0.270
PEOU4	-0.342	0.433	-0.661	0.500	**0.834**	0.414	0.375	0.284	0.388	-0.205	-0.109	0.277
CPA1	-0.548	0.532	-0.668	0.738	0.524	**0.917**	0.643	0.418	0.732	-0.355	-0.057	0.430
CPA2	-0.518	0.519	-0.687	0.729	0.540	**0.918**	0.633	0.412	0.683	-0.391	-0.097	0.464
CPA3	-0.505	0.598	-0.712	0.808	0.581	**0.939**	0.669	0.428	0.766	-0.414	-0.153	0.504
CPA4	-0.409	0.391	-0.454	0.549	0.325	**0.720**	0.488	0.427	0.428	-0.250	0.010	0.317
BNA1	-0.356	0.471	-0.499	0.591	0.476	0.631	**0.850**	0.518	0.538	-0.327	-0.142	0.203
BNA2	-0.411	0.486	-0.448	0.530	0.412	0.606	**0.818**	0.452	0.464	-0.315	-0.149	0.244
BNA3	-0.255	0.250	-0.242	0.386	0.266	0.391	**0.728**	0.518	0.357	-0.051	-0.060	-0.049
ITA1	-0.080	0.494	-0.376	0.365	0.382	0.326	0.461	**0.842**	0.361	-0.195	-0.080	0.089
ITA2	-0.186	0.447	-0.277	0.336	0.351	0.329	0.419	**0.810**	0.290	-0.222	-0.064	0.132
ITA3	-0.150	0.474	-0.267	0.358	0.353	0.438	0.483	**0.794**	0.316	-0.187	0.045	0.176
ITA4	-0.241	0.450	-0.269	0.396	0.331	0.409	0.568	**0.726**	0.388	-0.231	-0.031	0.080
AAI1	-0.548	0.481	-0.629	0.825	0.535	0.761	0.581	0.413	**0.971**	-0.338	-0.089	0.331
AAI2	-0.531	0.498	-0.629	0.814	0.560	0.732	0.577	0.441	**0.983**	-0.347	-0.115	0.307
AAI3	-0.505	0.467	-0.610	0.819	0.529	0.733	0.539	0.404	**0.981**	-0.330	-0.071	0.324
SIZE1	0.210	-0.434	0.406	-0.394	-0.293	-0.409	-0.322	-0.262	-0.346	**1.000**	0.510	-0.511
TIME1	0.004	-0.155	0.213	-0.142	-0.084	-0.093	-0.155	-0.041	-0.094	0.510	**1.000**	-0.171
RCMA1	-0.319	0.363	-0.400	0.422	0.330	0.494	0.195	0.149	0.328	-0.511	-0.171	**1.000**

6.5.4 ANCOVA RESULTS

Since we predicted the direct impact of the experimental treatments on multiple dependent variables (i.e., perceived strategy restrictiveness, perceived agent transparency, perceived cognitive effort, decision time, and consideration set size), MANCOVA was applied first to test whether the experimental treatments have an overall impact on these dependent variables (Hair et al., 1998). This study also tested several control variables as described in section 6.4.2. Since only the four dispositional trust beliefs (competence, benevolence, integrity, and trusting stance) are significantly correlated with some of these dependent variables, only these four controls are included in MANCOVA, and in the ANCOVA thereafter.

The MANCOVA results are presented in table 6-10. Overall significant main effects of both explanation use and decision strategy support were revealed, which allows us to examine the impact of explanation use and decision strategy support on the individual dependent variables via ANCOVA.

Table 6-10 MANCOVA Results				
	Wilks' Lambda	DF	F-Value	P-Value
Explanation Use	0.781	5, 138	7.72	**<0.001**
Decision Strategy Support	0.748	10, 276	4.30	**<0.001**
Explanation * Decision Strategy Support	0.944	10, 276	0.80	0.63
Dispositional Trust – Competence (DTC)	0.947	5, 138	1.54	0.18
Dispositional Trust – Benevolence (DTB)	0.966	5, 138	0.98	0.43
Dispositional Trust – Integrity (DTI)	0.992	5, 138	0.23	0.95
Dispositional Trust – Trusting Stance (DTT)	0.942	5, 138	1.71	0.14

6.5.4.1 PERCEIVED STRATEGY RESTRICTIVENESS

The ANCOVA results for the impact on perceived strategy restrictiveness are shown in table 6-11. Decision strategy support exerts a significant and negative impact on consumers' perceived strategy restrictiveness of online recommendation agents. To

compare the three types of agents, a Scheffe test for multiple comparisons was conducted (table 6-12) and the results indicate that differences between Hybrid agents and EBA agents and between AC agents and EBA agents are significant, while the difference between Hybrid agents and AC agents is not. Therefore, hypothesis H6-1(b) is supported while H6-1(a) and H6-1(c) are not.

Table 6-11 ANCOVA Results (DV: Perceived Strategy Restrictiveness)					
Source	DF	Sum of Squares	Mean Square	F	p-value
Explanations	1	0.86	0.86	0.97	0.33
Decision Strategy Support	2	15.40	7.70	8.68	**<0.001**
Explanations * Decision Strategy Support	2	6.58	3.29	3.71	**0.03**
Trust Propensity – Competence (covariate)	1	2.92	2.92	3.294	.072
Trust Propensity – Benevolence (covariate)	1	<0.01	<0.01	<0.01	.943
Trust Propensity – Integrity (covariate)	1	<0.01	<0.01	<0.01	.960
Trust Propensity – Trusting Stance (covariate)	1	.36	.36	.405	.525
Error	146	129.52	.88		

Table 6-12 Scheffe Comparisons for Perceived Strategy Restrictiveness			
Group A	Group B	Mean Difference (A – B)	Significance
Hybrid Agent	AC Agent	0.07	0.94
	EBA Agent	-0.58	**0.008**
AC Agent	Hybrid Agent	-0.07	0.94
	EBA Agent	-0.65	**0.003**

Table 6-11 also shows that a significant interaction effect occurs between decision strategy support and explanation use. Figure 6-4 compares the perceived strategy restrictiveness levels among the three types of agents in the conditions of "with"

explanations vs. "without" explanations. With explanation use, the level of perceived strategy restrictiveness is lowest in Hybrid agents and increases in the order of AC agents and EBA agents, while, without explanations, the level of perceived strategy restrictiveness is lowest in AC agents.

To test H6-2, we conducted two separate ANOVAs with Scheffe comparisons: one in the "with" explanation conditions and the other in the "without" explanation conditions. In the "with" explanation conditions, decision strategy support exerts a significant main effect ($p < 0.001$) while in the "without" explanations conditions, it has no significant main effect ($p > 0.1$). The Scheffe test in the "with" explanation conditions shows that the differences between Hybrid agents and EBA agents as well as between AC agents and EBA agents are significant, while the difference between Hybrid agents and AC is not (see table 6-13). Therefore, hypothesis H6-2(a) is partially supported. None of the Scheffe comparisons in the "without" explanation conditions are significant (see table 6-14). Therefore, Hypothesis H6-2(b) is supported.

Figure 6-4 Perceived Strategy Restrictiveness
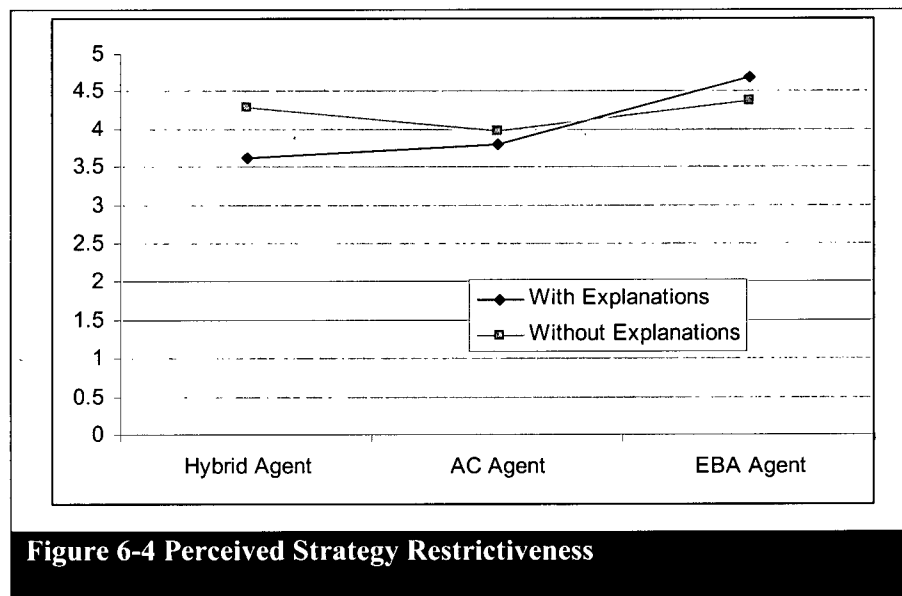
Table 6-13 Scheffe Comparisons for Perceived Strategy Restrictiveness, with explanations			
Group A (with explanations)	Group B (with explanations)	Mean Difference (A – B)	Significance
Hybrid Agent	AC Agent	-0.17	0.79
	EBA Agent	-1.07	**<0.001**
AC Agent	Hybrid Agent	0.17	<0.79
	EBA Agent	0.90	**0.003**

Table 6-14 Scheffe Comparisons for Perceived Strategy Restrictiveness, without explanations			
Group A (without explanations)	Group B (without explanations)	Mean Difference (A – B)	Significance
Hybrid Agent	AC Agent	0.31	0.46
	EBA Agent	-0.10	0.93
AC Agent	Hybrid Agent	-0.31	0.46
	EBA Agent	-0.40	0.27

6.5.4.2 PERCEIVED AGENT TRANSPARENCY

The ANCOVA results for the impact of decision strategy support and explanation use on perceived agent transparency are shown in table 6-15. A significant and positive main effect of explanation use is detected on perceived agent transparency. Therefore, hypothesis H6-5 is supported.

Table 6-15 ANCOVA Results (DV: Perceived Agent Transparency)					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Explanations	1	28.43	28.43	24.34	**<0.001**
Decision Strategy Support	2	2.43	1.22	1.04	0.36
Explanations * Decision Strategy Support	2	2.81	1.41	1.20	0.30
Trust Propensity – Competence (covariate)	1	1.34	1.34	1.15	0.29
Trust Propensity – Benevolence (covariate)	1	3.17	3.17	2.72	0.10
Trust Propensity – Integrity (covariate)	1	1.09	1.09	.93	0.34
Trust Propensity – Trusting Stance (covariate)	1	<0.001	<0.001	<0.001	0.99
Error	146	170.51	1.17		

Nevertheless, neither the interaction effect between decision strategy support nor the main effect of decision strategy support is significant (also see figure 6-5). The use of explanations uniformly increases perceived agent transparency; regardless of whether or not explanations are provided, the perceived agent transparency levels are similar across the three agents. Therefore, H6-6 (a) is supported, while H6-6(b) is partially supported.

Figure 6-5 Perceived Agent Transparency
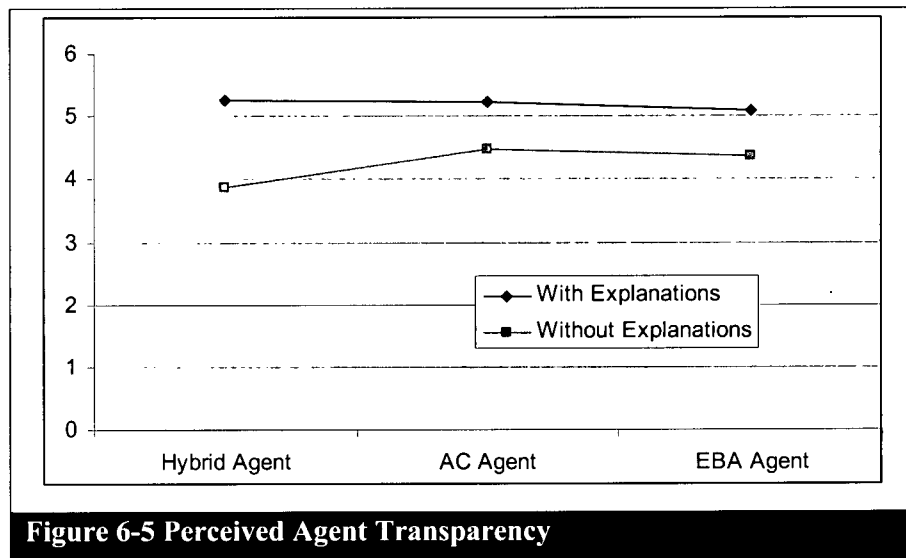
6.5.4.3 COGNITIVE EFFORT

Three variables were used to measure cognitive effort: consideration set size, decision time, and perceived cognitive effort. The ANCOVA results for these three variables are presented in tables 6-16 to 6-18, respectively. The group means are shown in figure 6-6 to 6-8.

Table 6-16 ANCOVA Results (DV: Consideration Set Size)					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F**	**p-value**
Explanations	1	188.15	188.15	0.84	0.36
Decision Strategy Support	2	310.66	155.33	0.69	0.50
Explanations * Decision Strategy Support	2	534.15	267.07	1.19	0.31
Trust Propensity – Competence (covariate)	1	149.59	149.59	0.67	0.42
Trust Propensity – Benevolence (covariate)	1	23.36	23.36	0.10	0.75
Trust Propensity – Integrity (covariate)	1	59.10	59.10	0.26	0.61
Trust Propensity – Trusting Stance (covariate)	1	91.06	91.06	0.41	0.53
Error	142	31843.34	224.24		

Table 6-17 ANCOVA Results (DV: Decision Time – minutes)

Source	DF	Sum of Squares	Mean Square	F	p-value
Explanations	1	451.08	451.08	2.19	.14
Decision Strategy Support	2	972.08	486.04	2.36	.10
Explanations * Decision Strategy Support	2	4.05	2.03	.01	.99
Trust Propensity – Competence (covariate)	1	209.63	209.63	1.02	.31
Trust Propensity – Benevolence (covariate)	1	4.471	4.471	.02	.88
Trust Propensity – Integrity (covariate)	1	36.68	36.68	.18	.67
Trust Propensity – Trusting Stance (covariate)	1	4.32	4.32	.02	.89
Error	146	30032.46	205.70		

Table 6-18 ANCOVA Results (DV: Perceived Cognitive Effort)

Source	DF	Sum of Squares	Mean Square	F	p-value
Explanations	1	0.06	0.06	0.05	0.83
Decision Strategy Support	2	23.05	11.52	8.82	**<0.001**
Explanations * Decision Strategy Support	2	5.62	2.81	2.15	0.12
Trust Propensity – Competence (covariate)	1	6.84	6.84	5.24	0.02
Trust Propensity – Benevolence (covariate)	1	0.21	0.21	0.16	0.69
Trust Propensity – Integrity (covariate)	1	0.01	0.01	0.01	0.94
Trust Propensity – Trusting Stance (covariate)	1	7.41	7.41	5.67	0.02
Error	146	190.72	1.31		

With respect to consideration set size and decision time, none of the main effects and interaction effects of explanation use and decision strategy support were significant. Therefore, H6-8 and H6-9 are not supported. To test H6-10 and H6-11, we also split the sample along the explanation dimension and conducted separate ANOVA with Scheffe tests. The only significant difference was found between the consideration set size of the Hybrid agents and the AC agents, when explanations were provided. The consideration set size for consumers using the Hybrid agents with explanations was significantly smaller than that for consumers using the AC agents with explanations (see figure 6-6). Therefore, H6-10(a) and H6-11(a) are partially supported and H6-10(b) and H6-11(b) are supported.

Figure 6-6 Consideration Set Size

Figure 6-7 Decision Time (minutes)

Figure 6-8 Perceived Cognitive Effort
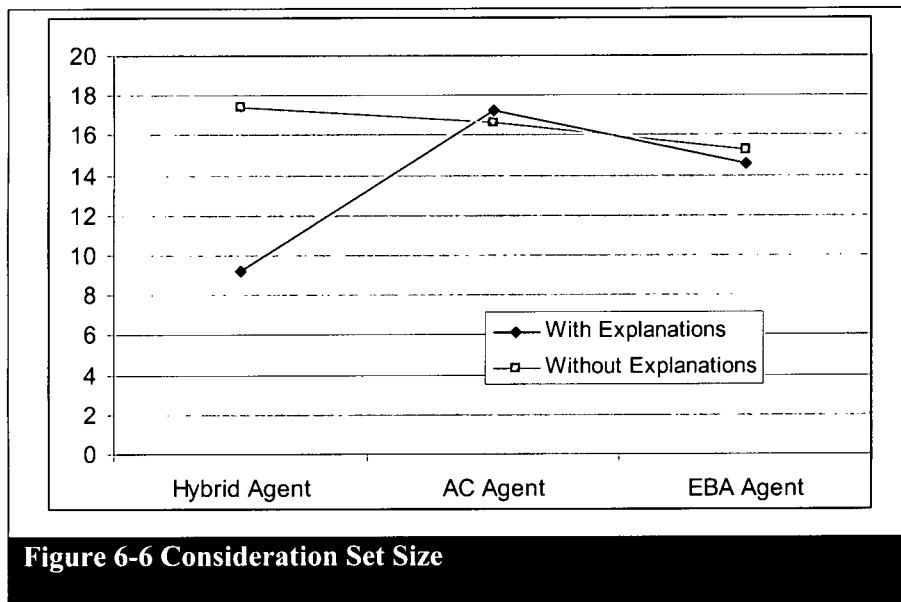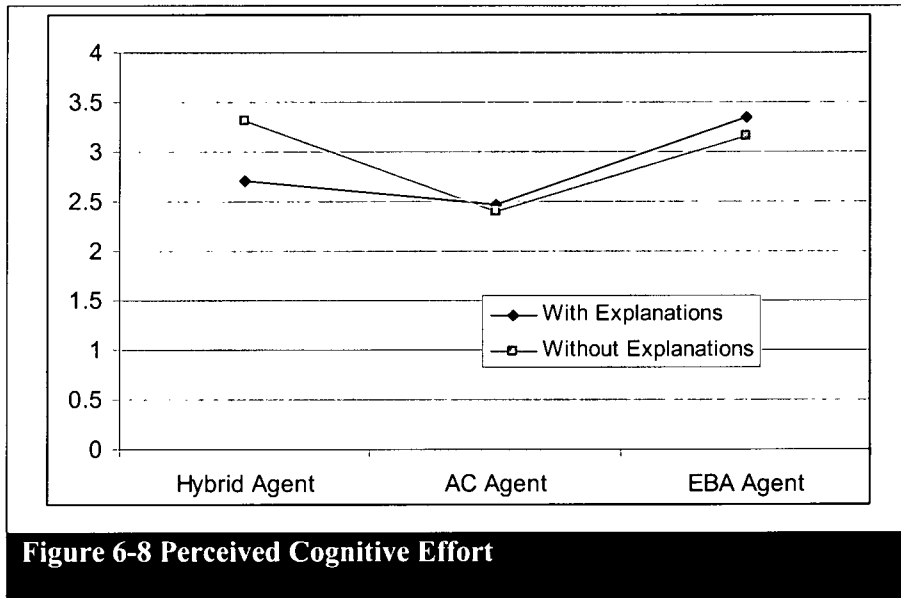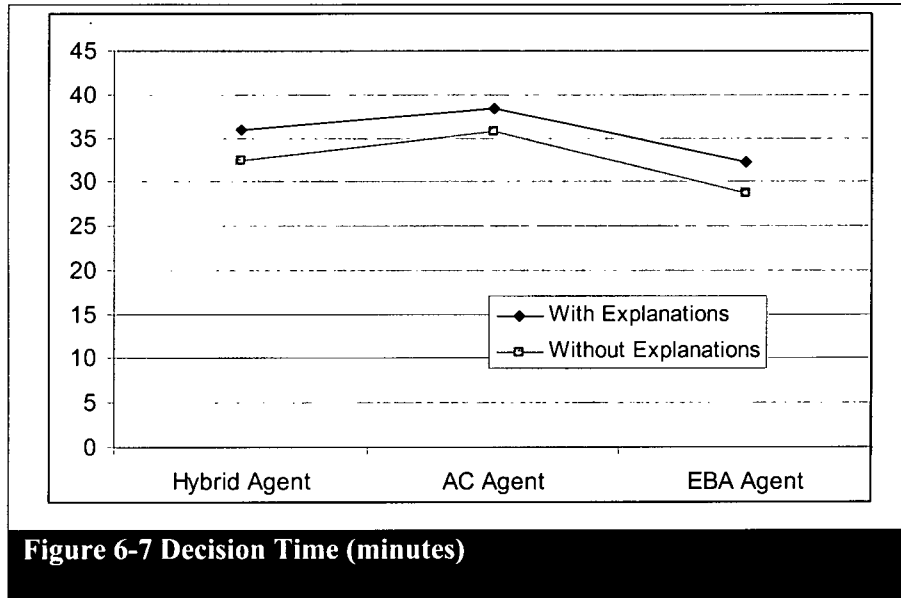
With regards to perceived cognitive effort, the main effect of decision strategy was significant, while the main effects of explanation use and the interaction effects were not. We also conducted two separate ANOVA tests with Scheffe comparisons in the "with" and "without" explanation conditions. In the "with" explanation condition, no significant difference was found between the Hybrid agents and the two other types of agents, but the perceived cognitive effort for the AC agents was significantly lower than for the EBA agents (table 6-19). Therefore, H6-12(a) is partially supported. In the "without" explanation conditions, a significant difference was found between the Hybrid

and the AC agents (table 6-20). Therefore, partial support was found for hypothesis H6-12(b).

To evaluate the impact of explanation use on perceived cognitive effort, we conducted three separate ANOVAs for the three types of agents. None of the impacts were found to be significant. Therefore, hypothesis H6-13(a), (b), and (c) were all supported.

Table 6-19 Scheffe Comparisons for Perceived Cognitive Effort, with explanations			
Group A (with explanations)	Group B (with explanations)	Mean Difference (A – B)	Significance
Hybrid Agent	AC Agent	0.24	0.76
	EBA Agent	-0.64	0.14
AC Agent	Hybrid Agent	-0.24	0.76
	EBA Agent	-0.88	**0.03**

Table 6-20 Scheffe Comparisons for Perceived Cognitive Effort, without explanations			
Group A (without explanations)	Group B (without explanations)	Mean Difference (A – B)	Significance
Hybrid Agent	AC Agent	0.92	**0.03**
	EBA Agent	0.15	0.90
AC Agent	Hybrid Agent	-0.92	**0.03**
	EBA Agent	-0.76	0.09

6.5.5 STRUCTURAL MODEL

In the structural model, the variable of explanation use was coded using a dummy variable[27]. The "without" explanation conditions were coded as "0" and the "with" explanation conditions were coded as "1". For decision strategy support, two dummy variables were used for the three types of agents: HYAC and HYEBA (table 6-21). These two dummy variables were used as formative indicators for the decision strategy support construct in the PLS structural model. For the interaction between explanation use and decision strategy support, two indicators are used to get the product of the two dummy variables for decision strategy support and the dummy variable for explanation use. Then, these two indicators were also modeled as formative indictors for the interaction construct in the structural model.

Table 6-21 Dummy Codes for Agent Types		
Agent Type	Dummy Variable	
	HYAC	HYEBA
Hybrid Agent	0	0
AC Agent	1	0
EBA Agent	0	1

Figure 6-9 shows the results of the structural model. For the direct impact of decision strategy support and explanation use, as well as the interaction effects, on perceived strategy restrictiveness, perceived agent transparency, and cognitive effort (decision time, consideration set size, and perceived cognitive effort), PLS delivers similar results as the ANCOVA results. Explanation use exerts significant main effects on perceived agent transparency while decision strategy support has significant main effects on perceived cognitive effort. The interaction effects on perceived strategies restrictiveness are also significant.

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[27] We thank Dr. Wynne Chin for the advice on the use of dummy variables for experimental treatment and interaction variables in PLS. The use of dummy variables in PLS appeared in other studies as well (e.g., Yoo and Alavi, 2001).

Perceived strategy restrictiveness is negatively and significantly correlated with both trust and the PU of agents. Therefore, H6-3 and H6-4 are supported. Perceived agent transparency is positively and significantly correlated with trust in agents, thus H6-7 is supported.

Regarding the impact of cognitive effort, only the perceived cognitive effort is negatively and significantly correlated with the PEOU of agents, while the two observed measures (decision time and consideration set size) are not significantly correlated with the POEU of agents. Therefore, H6-14(a) is supported but neither H6-14(b) nor (c) is supported.

The Trust-TAM part of the model generated the same conclusions as those in chapter 4. The only non-significant correlation is between PEOU and intentions to adopt agents. Both the PU and trust positively and significantly influence the intentions to adopt agents. PEOU positively and significantly influences both PU and trust. Trust also positively and significantly influences PU. Therefore, H6-15, H6-17, H6-18, H6-19, and H6-20 are supported, while H6-16 is not supported.

A summary of hypotheses testing from both the ANCOVA and PLS analyses are provided in table 6-22.
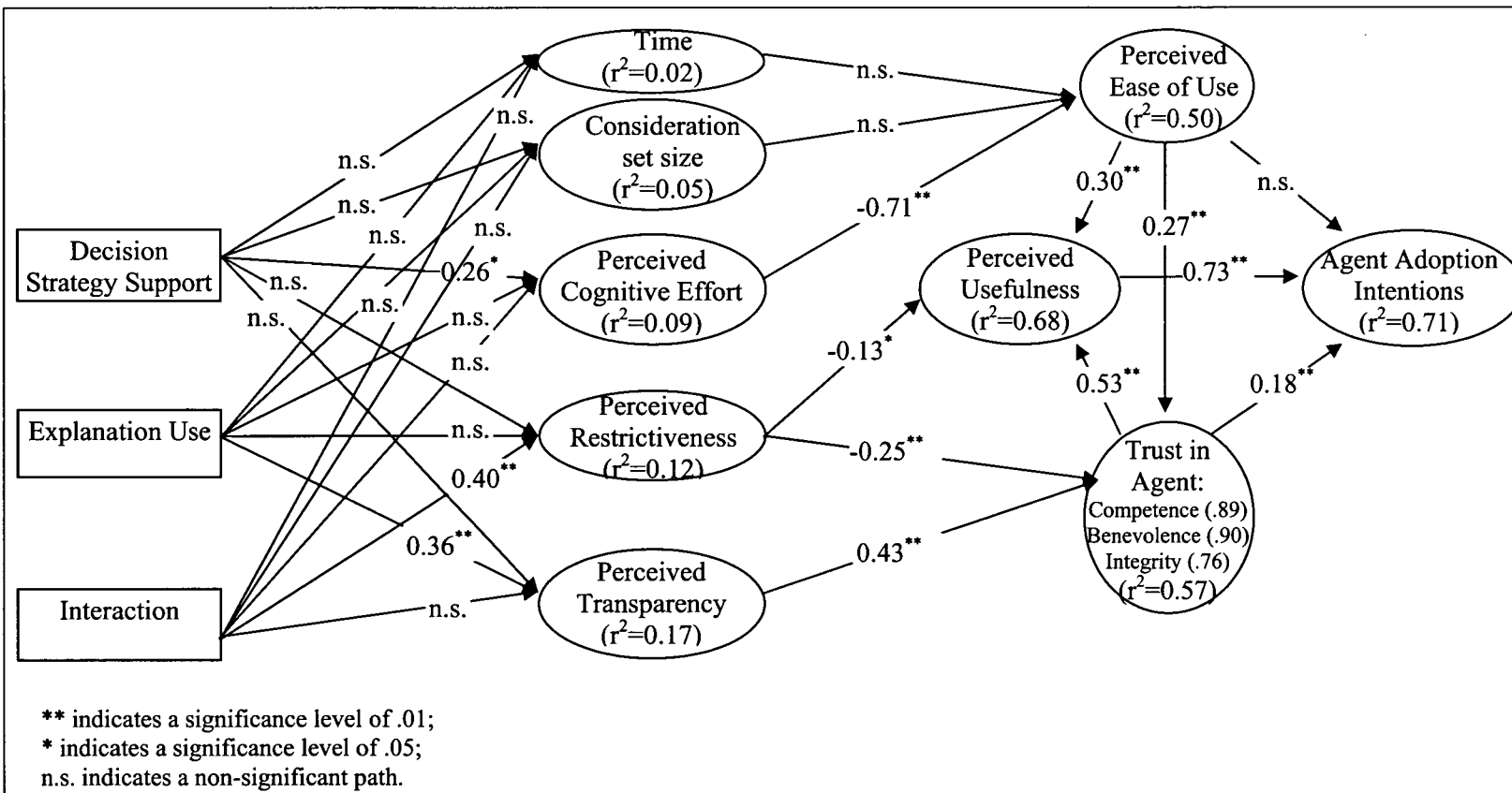
Figure 6-9 PLS Structural Model Testing Results

** indicates a significance level of .01;
* indicates a significance level of .05;
n.s. indicates a non-significant path.

Table 6-22 A Summary of Hypothesis Testing Results	
Hypothesis	**Supported?**
H6-1a: Hybrid agents will be perceived to be less restrictive than AC agents.	*No (a)*
H6-1b: Hybrid agents will be perceived to be less restrictive than EBA agents.	*Yes (b)*
H6-1c: AC agents will be perceived to be as restrictive as EBA agents.	*No (c)*
H6-2a: With explanation use, Hybrid agents will be perceived to be less restrictive than AC or EBA agents; AC agents will be perceived to be as restrictive as EBA agents. **H6-2b**: Without explanations, Hybrid agents will be perceived to be as restrictive as AC and EBA agents.	*Partially (a)* *Yes (b)*
H6-3: Perceived agent restrictiveness will negatively influence consumers' trust in online recommendation agents.	*Yes*
H6-4: Perceived agent restrictiveness will negatively influence consumers' PU in online recommendation agents.	*Yes*
H6-5: Use of explanations will increase consumers' perceived agent transparency of online recommendation agents.	*Yes*
H6-6a: With explanation use, Hybrid agents will be perceived as being transparent as AC or EBA agents. **H6-6b**: Without explanations, Hybrid agents will be perceived to be less transparent than AC or EBA agents; AC agents will be perceived to be as equally transparent as EBA agents.	*Yes (a)* *Partially (b)*
H6-7: Perceived agent transparency will positively influence consumer trust in online recommendation agents.	*Yes*
H6-8: The use of explanations reduces consumers' consideration size when using recommendation agents (H6-8a: Hybrid agents, H6-8b: AC agents, H6-8c: EBA agents).	*No (a)* *No (b)* *No (c)*
H6-9: The use of explanations reduces consumers' decision time when using recommendation agents (H6-9a: Hybrid agents, H6-9b: AC agents, H6-9c: EBA agents).	*No (a)* *No (b)* *No (c)*
H6-10a: With explanation use, the consideration set size of consumers using Hybrid agents will be smaller than that of consumers using AC agents or EBA agents; the consideration set size of consumers using AC agents will be similar to that of consumers using EBA agents. **H6-10b**: Without explanations, the consideration set size of consumers using the Hybrid agents will be as similar to that of consumers using AC and EBA agents.	*Partially (a)* *Yes (b)*
H6-11a: With explanation use, the decision time of consumers using Hybrid agents will be smaller than that of consumers using AC agents or EBA agents; the decision time of consumers using AC agents will be similar to that of consumers using EBA agents. **H6-11b**: Without explanations, the decision time of consumers using Hybrid agents will be similar to that of consumers using AC and EBA agents.	*Partially (a)* *Yes (b)*

Table 6-22 A Summary of Hypothesis Testing Results (cont'd)	
H6-12a: With explanation use, the perceived cognitive effort in consumers using Hybrid agents will be similar to that of consumers using AC agents or EBA agents.	*Partially (a)*
H6-12b: Without explanations, the perceived cognitive effort of consumers using Hybrid agents will greater than that of consumers using AC agents or EBA agents; the perceived cognitive effort of consumers using AC agents will be similar to that of consumers using EBA agents.	*Partially (b)*
H6-13: Use of explanations will not influence consumers' perceived cognitive effort in using recommendation agents (H6-13a: Hybrid agents, H6-13b: AC agents, H6-13c: EBA agents).	*Yes (a)* *Yes (b)* *Yes (c)*
H6-14: Perceived cognitive effort (H6-14a), consideration size set (H6-14b), and decision time (H6-14c) will negatively influence consumers' PEOU of recommendation agents.	*Yes* *No* *No*
H6-15: PU of recommendation agents will positively affect consumers' intentions to adopt the agents.	*Yes*
H6-16: PEOU of recommendation agents will positively affect consumers' intentions to adopt the agents.	*No*
H6-17: PEOU of recommendation agents will positively affect PU of the agents.	*Yes*
H6-18: Trust in recommendation agents will positively affect consumers' intentions to adopt the agents.	*Yes*
H6-19: Trust in the recommendation agents will positively affect PU of the agents.	*Yes*
H6-20: PEOU of recommendation agents will positively affect consumers' trust in the agents.	*Yes*

6.6 Discussion

This study provides strong evidence to support the important and differential roles of user perceptions of strategy restrictiveness, agent transparency, and cognitive effort in influencing the antecedents in Trust-TAM: PU, PEOU, and trust. Also, the total effects of these three perceptions on consumers' intentions to adopt an agent were calculated, as were the effects on the three antecedents in Trust-TAM. The total effects are operationalized as the sum of direct effects (standardized path coefficients) and indirect effects (productions of corresponding standardized path coefficients) (Barclay et al., 1995). The results show that perceived agent transparency exerts the highest impact on trust in an agent; perceived strategy restrictiveness has the greatest influence on PU of an agent; and perceived cognitive effort mostly influences PEOU of an agent (table 6-23).

Table 6-23 Total Effects (Direct and Indirect) on Intentions to adopt agents, Trust, PU, and PEOU				
Perceptions	**Adoption Intentions**	**Trust**	**PU**	**PEOU**
Perceived Cognitive Effort	0.19	0.19	0.24	**0.71**
Perceived Strategy Restrictiveness	0.24	0.25	**0.49**	--
Perceived Agent Transparency	0.24	**0.43**	0.23	--

In addition, more than 50% of the variances in all the antecedents in Trust-TAM explained by the three user perceptions, and 71% of the variance in intention to adopt an agent is explained by the three antecedents (Figure 6-9). Thus, the research model is successful in identifying important factors that influence user adoptions of agents as well as their antecedents.

Overall, the experimental treatments successfully manipulated the above three important perceptions. As predicted, regarding perceived agent strategy restrictiveness, an interaction effect was detected between decision strategy support and explanation use. The benefits of Hybrid agents can only be achieved when explanations are provided. For example, without explanations, the levels of perceived strategy restrictiveness of the three types of agents are the same (H6-2b). Therefore, it is concluded that explanations should

accompany the provision of decision strategy capabilities in an agent so that consumers can easily understand the features and apply them properly.

One of the key predictions that was not well supported is the difference between Hybrid agents and AC agents. We did not find a significant difference in perceived strategy restrictiveness for these two types of agents (H6-1a). One possible reason is that the cognitive effort needed in using the Hybrid agents is higher than that for AC agents. Different types of effort are involved in making a choice, decision aided by a recommendation agent (e.g., Todd and Benbasat, 1991), such as the effort in learning and using agent features, and the effort in examining recommendations from the agent. Although the consideration set size of participants using Hybrid agents with explanations was significantly smaller than that of participants using AC agents with explanations (H6-10a), the levels of perceived cognitive effort were the same for participants using either of these two types of agents (H6-12a). Therefore, the cognitive effort in learning and using Hybrid agents is quite high, as was estimated in the NGOMSL analyses. Consumers need to spend extra effort to learn and understand the strategy choice and employ their control.

According to the cognitive effort perspective in the behavioral decision theories studied in DSS (Todd and Benbasat, 1991; 1992; 1994a; 1994b; 2000), the conservation of effort is more important than increases in decision quality. Therefore, the high effort involved in using the Hybrid agents might have prevented participants from fully utilizing the agent features. An empirical study by Todd and Benbasat (2000) showed that decision aids can induce the use of normative oriented strategies when the normative strategy is easier to execute than competing alternative strategies. Similarly, it is concluded that additional features provided by an agent will not be effective unless the cognitive effort in learning and using these features is low.

We also found a significant difference in perceived strategy restrictiveness between AC agents and EBA agents (table 6-11). AC agents were perceived to be less restrictive than EBA agents, indicating that participants perceived that AC agents provide a higher level of decision process support than EBA agents do.

As discussed in section 6.2.1. The AC strategy provides superior recommendations, compared to the EBA strategy (e.g., Todd and Benbasat, 1999). In addition, the perceived cognitive effort of participants using EBA agents is significantly higher than for participants using AC agents (Table 6-23), though the NGOMSL analyses shows that EBA agents require less effort than AC agents. The review of the recorded videos from the experiment shows that on average participants used the AC agents 4.6 times while they used the EBA agents 8.6 times, to obtain a proper set of recommendations. It was counted once when participants used the agent to get recommendations or whenever they returned back to the agent-user dialogue page, changed their answers and got recommendations again. For a shopping task, the agents were often used repeatedly, and the EBA agents were used more times than the AC agents, leading to higher cognitive effort in using EBA agents. Again, AC agents are superior to EBA agents, not only because of the high quality of recommendations but also because of the lower effort needed to use them.

6.7 Limitations, Contributions, and Future Research

6.7.1 LIMITATIONS AND FUTURE RESEARCH

A number of limitations are involved with this study, including some that are in common with Experiment 1, such as common method bias, testing content-filtering and needs based agents only, and using university students as the testing sample. Regarding the common method bias issues, we applied Harmon's one-factor test to the data from the current experiment (Podsakoff and Organ, 1986). An exploratory factor analysis was conducted on all dependent variables except for objective variables, but no single factor was observed and no single factor accounted for a majority of the covariance in the variables. This suggests that common method bias is not a concern in the present study.

Another limitation that should be pointed out is the fact that this study only investigates one type of agent restrictiveness, namely, strategy restrictiveness. Other types of restrictiveness exist, as proposed by Silver (1990), such as communication

restrictiveness related to the set of questions and its sequence in the agent-user dialogues. An agent may or may not allow a consumer to choose a sub-set of questions to answer, and the questions in the agent-user dialogue could be in a fixed order or could be answered according to the user's preferences. These features could also influence a consumers' perceived restrictiveness of an agent but in different ways. Future research is needed to examine these differential impacts. Also, the investigation should be conducted at the optimum level of agent restrictiveness. As pointed out by Silver (1990), with too little restrictiveness, users could become overloaded in making choices.

A second future research area is to further reduce the cognitive effort in using the Hybrid agents. As discussed earlier, this may explain why Hybrid agents were not as effective as expected. To reduce the cognitive effort, for example, a default strategy could be used in the strategy choice so that consumers do not need to spend an extra effort in choosing the strategy, even though they are allowed to do so. Since the AC strategy is closest to a normative strategy (Todd and Benbasat, 1999), and given that AC agents perform better on most of the dependent variables than the EBA agents, the default strategy could be set to the AC strategy, to gain more benefits from using the Hybrid agent. Future research could help to examine whether or not reducing the cognitive effort in using Hybrid agents can generate more benefits.

Third, this study focuses on consumers' initial trust based on their first time use of an un-branded recommendation agent. The effects of decision strategy support and explanation facilities on consumers' trust and adoption of online recommendation agents remain unclear when consumers have repeated interactions with the agents. The generalizability of results to consumers who have experience with agents is not immediately obvious and warrants future research. Also, the impact of brand name of online vendors and the reputation of recommendation agent were not examined in this study and deserve future research.

Lastly, this study examined users' intentions to adopt recommendation agents to get product recommendations, but it did not explore how consumers act upon the recommendations from the agents. It remains unclear how consumers' purchase behavior

will be influenced by the use of recommendation agents. For example, future research is needed to examine whether or not consumers are more willing to follow the recommendations and purchase the recommended products if they perceive the recommendation agents to be more useful and trustworthy.

6.7.2 CONTRIBUTIONS

Notwithstanding these limitations, this study makes significant contributions to both research and practice. The main contribution of this study to research is two-fold. First, this study empirically investigates an important feature for trustworthy online recommendation agents – agent restrictiveness. In particular, the impact of agent decision strategy support on agent restrictiveness was examined and its important roles were confirmed. By enabling consumers to control over and configure agent decision strategies, recommendation agents can adapt to different consumers' needs and are perceived to be less restrictive. A certain level of user control is desirable in the agent applications, especially because of the high risk and uncertainties in online shopping (Gefen et al., 2003b). User control over an agent can help to reduce such uncertainties and increase the user's trust in the agent. A new measure for perceived strategy restrictiveness was developed and, to our knowledge, this is the first empirical study to test its impact on consumers' trust and PU of the agents.

Second, in addition to perceived agent restrictiveness, the impacts of agent transparency and cognitive effort on consumer trust and PEOU of the agents were also empirically tested. Although system transparency has been generally discussed in the IS literature (Gregor and Benbasat, 1999; Silver, 1991a), empirical examination of its impact and antecedents is lacking. More importantly, together with perceived strategy restrictiveness, this study reveals the relative importance of these variables on the important antecedents in Trust-TAM. As suggested by Davis (1989), the factors that influence the antecedents of user acceptance of a technology need to be identified, as done in this study.

This study also has significant implications for practitioners. Most recommendation agents that are currently applied in various websites use predefined decision strategies. To our knowledge, the design of flexible and malleable strategies used by an agent is largely unexplored. In online environments, user control helps to reduce risk and uncertainty perceptions and increase consumers' trust levels (Das and Teng, 1998). When a recommendation agent is provided by an unfamiliar e-vendor, a loss of control is one of the main obstacles in the initial trust formation (Das and Teng, 1998). Reducing agent restrictiveness by allowing users to have control over an agent (e.g., allowing users to choose different decision strategies) can deal with such obstacles, thus it facilitate users' trust in the agent.

By considering both the benefits and costs of reduced agent restrictiveness for consumers, this study provides practical guidelines for the design of flexible agent strategies. This chapter investigates the interaction effects of explanation facilities and decision strategy support on perceived agent transparency, strategy restrictiveness, and cognitive effort. The results inform designers that effective user control and additional agent features require that: 1) a set of appropriate explanations should be provided so that users can understand these features and employ them properly, and 2) using these features should not induce much cognitive effort so that users are willing to use them. The results of this study and Experiment 1 show that the use of *how* explanations, *why* explanations, and *guidance* significantly increases the perceived transparency levels of an agent and enhances consumers' trusting beliefs in the agent. To reduce the effort to employ user control, as discussed earlier, default settings might be used. They can be set by a normative strategy (e.g., AC strategy for the strategy choice), or inferred from user background and previous interaction history. A transparent agent with additional features, that empowers user control, but does not require much additional effort, delivers more benefits to users (e.g., more useful and trustworthy) and can provide more effective recommendation services, leading to a higher chance of user adoption.

Appendices

APPENDIX 6-1 SCREEN SHOTS FOR EXPERIMENTAL AGENTS

- A question in the agent-user dialogue for the Hybrid agents with explanations:

Figure A6-1 (a) Question Page for Hybrid Agents

- When the "non-essential preference" option is chosen in the Hybrid agents with explanations:

Figure A6-1(b) Question Page for Hybrid Agents – "Non-Essential Preference" Chosen

- When the "essential preference" option is chosen in the Hybrid agents with explanations:

Figure A6-1 (c) Question Page for Hybrid Agents – "Essential Preference" Chosen

- When the *how* explanation was clicked and presented for the Hybrid agents with explanations:

Figure A6-1 (d) Question Page for Hybrid Agents – *How* Explanation Shown

- When the *guidance* on "non-essential" versus "essential" was clicked and presented in the Hybrid agents with explanations:

3) How far will you be from most of the subjects that you photograph?

1) Immediate vicinity

How

Why

Guidance

- 2) A moderate distance or less

3) Far away, in addition to immediate and moderate vicinity

Reset

Non-Essential Preference   OR   Essential Preference

Guidance on Non-Essential versus Essential

Importance of this criterion

1 2 3 4 5 6 7 8 9

Low   High

Explanation/Guidance

I will use different approaches to make recommendations based on your choice of 'non-essential' or 'essential' preference. If you want me to recommend only those cameras that exactly satisfy your desired choice to this question, please select the 'essential preference'. On the contrary, if you want me to recommend all cameras that fit your overall preferences quite well but might not exactly satisfy your desired choice to this question, please select the 'non-essential preference'.

Please be advised that choosing 'essential preference' or very high importance levels in the 'non-essential preference' will significantly reduce the amount of recommendations that I could provide.

Figure A6-1 (e) Question Page for Hybrid Agents – *Guidance* on Strategy Shown

- A question in the agent-user dialogue for the AC agents with explanations:

Budget / Brand   Main Features   Preferences   Extras

Distance   Printing   Camera Size   Get Recommendations

4) What are you going to do with your pictures?

1) Save them in electronic formats only

How

Why

Guidance

- 2) Print pictures in sizes around 5" x 7", in addition to saving them in electronic formats

3) Print pictures in larger sizes (at least 8" x 10"), in addition to saving them in electronic formats

Reset

Importance of this criterion

1 2 3 4 5 6 7 8 9

Low   High

Explanation/Guidance

Figure A6-1(f) Question Page for AC Agents

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- A question in the agent-user dialogue for the EBA agents with explanations:

Figure A6-1 (g) Question Page for EBA Agents

- Recommendation page after the agent-user dialogues of the Hybrid and AC agents with explanations:

Figure A6-1 (h) Result Page for Hybrid Agents and AC Agents

- When the *how* explanation was clicked and presented in the recommendation page of the Hybrid agents and AC agents with explanations:
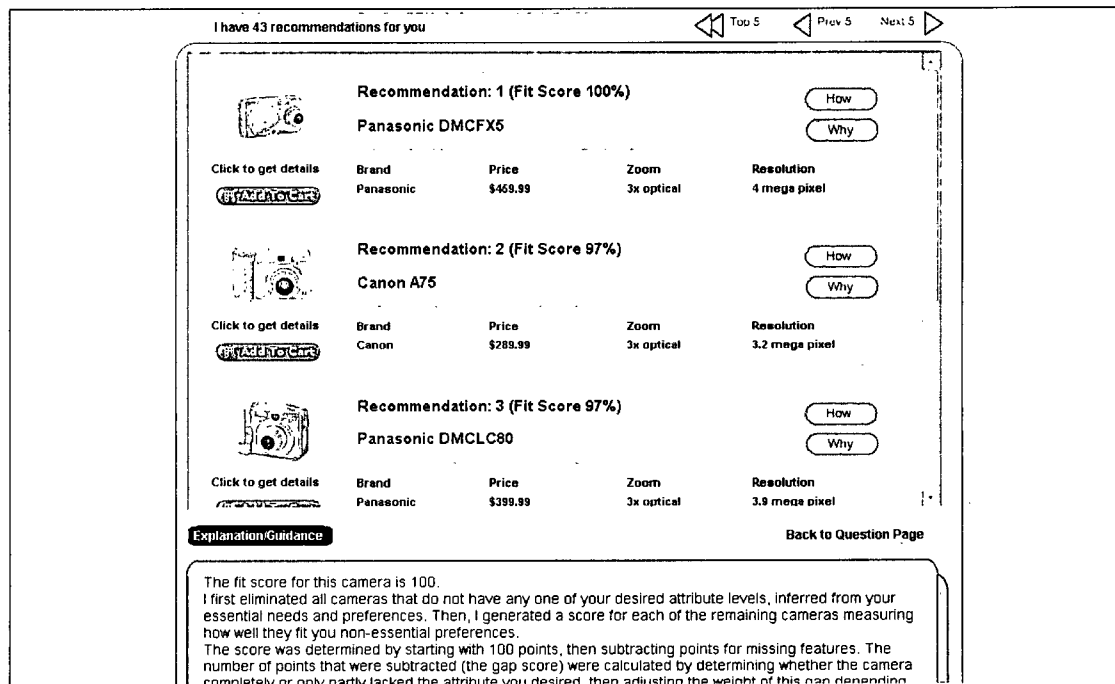

Figure A6-1 (i) Result Page for Hybrid Agents and AC Agents – *How* Explanation Shown

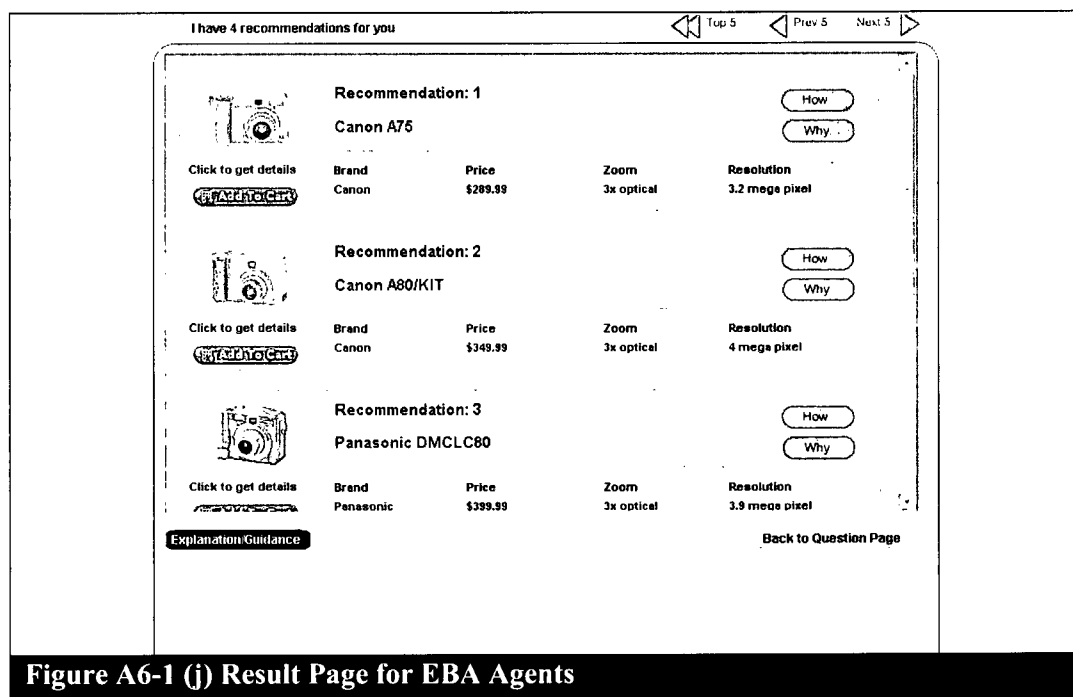- Recommendation page after the agent-user dialogues of the EBA agents with explanations:

Figure A6-1 (j) Result Page for EBA Agents

APPENDIX 6-2 NATURAL GOMS LANGUAGE ANALYSES

Natural GOMS Language (NGOMSL) was developed as a cognitive modeling method by Kieras (1997). It is based on GOMS models, which have been used by software designers to model user behavior in terms of *Goals*, *Operators*, *Methods* and *Selection rules*. According to Kieras (1997), goals are what users are trying to accomplish. Methods are a series of procedures that describe how to accomplish goals. The procedures consist of operators that are elementary actions to accomplish the goals. If more than one method is available to accomplish a goal, selection rules specify which method should be used to reach a given goal. A family of GOMS models has been successfully applied in many practical design problems (Kieras, 1997).

Among the various GOMS models, NGOMSL has been widely used to predict the execution and learning time for users to carry out a task with a system. Accordingly, we use NGOSML to predict the execution time of using recommendation agents as a measure of the users' effort to use the agents.

Based on Kieras (1997), execution time can be predicted by summing the NGOMSL statement time, primitive operator time, mental operator time, and waiting time. Execution time for each NGOMSL statement time is 0.1 second. Waiting time is set to 0 because the retrieval of information is almost instantaneous in this study. The times for different operators are as suggested by Kieras (1997) (see table A6-1). Our experimental recommendation agents do not require using a keyboard, so that only two standard operators and the mentor operator are needed.

Table A6-1 Relevant Operators in this Study		
Operators	User Activity	Time (sec.)
P	Point with mouse to a target on the display	1.1
BB	Pushing and releasing mouse button rapidly	0.2
M	Mental act of thinking or perception	1.2

The assumptions for our NGOMSL analyses are as follows:

- Participants are average non-secretary typists.
- Participants use recommendation agents.
- The hyperlink for a recommendation agent is visible on the webpage presented to participants.
- All questions are answered in the agent-user dialogues.
- Participants use the agent once and do not change their answers in a back-and-forth manner.
- Answering a question to express a user's needs and preferences requires four mental operators since the user needs to read a question and the three options for each question.
- Participants do not need to find the options for a question as they are presented together with the question.
- For AC or Hybrid agents, participants do not need to find the location of importance levels as they are presented together with the question.
- Hands begin and end on the mouse.

The detailed NGOMSL analyses for AC agents, EBA agents, and Hybrid agents are described in tables A6-2, A6-3, and A6-4. The analyses are based on a decision task that involves r number of questions (attributes). In our agent interface, four categories of questions are presented (i.e., "Budget/Price," "Main Features," "Preferences," and "Extra;" see figures in appendix 6-1). Under each category, several attribute buttons can be found (two buttons for "Budget / Price," three buttons for "Main Features," four buttons for "Preferences," and two buttons for "Extra"). By clicking on a button, a question is presented below it to elicit the user's needs and preferences.

AC agents involve $(31+17r)$ statements, $(5+3r)$ P, $(5+3r)$ BB, and $(10+7r)$ M operators (see table A6-2). AC agents have seven high-level goals to be accomplished: 1) choosing the agent to find a product alternative, 2) choosing categories of questions, 3) choosing attributes to express their needs and preferences, 4) answering the questions to express their needs and preferences, 5) assigning importance weights to attributes, 6)

deciding whether or not more attributes are to be chosen, and 7) deciding whether or not more categories of questions are to be presented. Users choose to use the agents once, while they need to repeatedly choose a category of questions and decide whether or not to continue in each category. Users need also repeatedly choose an attribute, answer the question, assign a weight of importance, and decide whether or not to continue for each attribute.

Table A6-2 NGOMSL Analyses for AC Agents

	Description	# of statements	Total # of statements	Type of operators	# of operators	Total # of operators
Method for goal – Choose a product alternative						
Step 1	Accomplish goal: choose the agent	1	1			
Step 2	Accomplish goal: choose a category of questions	1	4			
Step 3	Accomplish goal: choose an attribute	1	r			
Step 4	Accomplish goal: answer the question	1	r			
Step 5	Accomplish goal: choose an importance level	1	r			
Step 6	Decide: if no more questions left, then return with sub-goal accomplished. Otherwise, go to step 3	1	r			
Step 7	Decide: if no more categories left, then return with goal accomplished. Otherwise, go to step 2	1	4			
Method for goal – choose the recommendation agent						
Step 1	Decide to choose the agent	1	1	M	1	1
Step 2	Find the agent link	1	1	M	1	1
Step 3	Point to the agent link	1	1	P	1	1
Step 4	Click the agent link	1	1	BB	1	1
Step 5	Return with goal accomplished	1	1			
Method for goal – choose a category of questions						
Step 1	Decide to choose a category	1	1	M	1	4
Step 2	Find the category	1	4	M	1	4
Step 3	Point to the category	1	4	P	1	4
Step 4	Click the category	1	4	BB	1	4
Step 5	Return with goal accomplished	1	4			
Method for goal – choose an attribute						
Step 1	Decide to choose an attribute	1	r	M	1	r
Step 2	Find the question	1	r	M	1	r
Step 3	Point to the question	1	r	P	1	r
Step 4	Click the question	1	r	BB	1	r
Step 5	Return with goal accomplished	1	r			
Method for goal – answer the question						
Step 1	Decide to answer the question	1	r	M	4	r
Step 2	Point to the option	1	r	P	1	r
Step 3	Click the option	1	r	BB	1	r
Step 4	Return with goal accomplished	1	r			
Method for goal – choose an importance level						
Step 1	Decide to choose level	1	r	M	1	r
Step 2	Point to the level	1	r	P	1	r
Step 3	Click the level	1	r	BB	1	r
Step 4	Return with goal accomplished	1	r			

EBA agents require (31+12r) statements, (5+2r) P, (5+2r) BB, and (10+6r) M operators (table A6-3). EBA agents have six, high-level goals to be accomplished: 1) choosing the agent to find a product alternative, 2) choosing categories of questions, 3) choosing desired attributes to express their needs and preferences, 4) answering the questions to express their needs and preferences, 5) deciding whether or not more attributes are available to choose, and 6) deciding whether or not more categories of questions to be presented. Users choose to use an agent once, but must repeatedly choose a category of questions and decide whether or not to continue, for each category. Also, they need to repeatedly choose an attribute, answer the question, and decide whether or not to continue, for each attribute.

Table A6-3 NGOMSL Analyses for EBA Agents						
	Description	# of statements	Total # of statements	Type of operators	# of operators	Total # of operators
Method for goal – Choose a product alternative						
Step 1	Accomplish goal: choose the agent	1	1			
Step 2	Accomplish goal: choose a category of questions	1	4			
Step 3	Accomplish goal: choose an attribute	1	r			
Step 4	Accomplish goal: answer the question	1	r			
Step 5	Decide: if no more questions left, then return with sub-goal accomplished. Otherwise, go to step 3	1	r			
Step 6	Decide: if no more categories left, then return with goal accomplished. Otherwise, go to step 2	1	4			
Method for goal – choose the recommendation agent						
Step 1	Decide to choose the agent	1	1	M	1	1
Step 2	Find the agent link	1	1	M	1	1
Step 3	Point to the agent link	1	1	P	1	1
Step 4	Click the agent link	1	1	BB	1	1
Step 5	Return with goal accomplished	1	1			
Method for goal – choose a category of questions						
Step 1	Decide to choose a category	1	1	M	1	4
Step 2	Find the category	1	4	M	1	4
Step 3	Point to the category	1	4	P	1	4
Step 4	Click the category	1	4	BB	1	4
Step 5	Return with goal accomplished	1	4			
Method for goal – choose an attribute						
Step 1	Decide to choose an attribute	1	r	M	1	r
Step 2	Find the question	1	r	M	1	r
Step 3	Point to the question	1	r	P	1	r
Step 4	Click the question	1	r	BB	1	r
Step 5	Return with goal accomplished	1	r			
Method for goal – answer the question						
Step 1	Decide to answer the question	1	r	M	4	r
Step 2	Point to the option	1	r	P	1	r
Step 3	Click the option	1	r	BB	1	r
Step 4	Return with goal accomplished	1	r			

Table A6-4 NGOMSL Analyses for Hybrid Agents

	Description	# of statements	Total # of statements	Type of operators	# of operators	Total # of operators
Method for goal – Choose a product alternative						
Step 1	Accomplish goal: choose the agent	1	1			
Step 2	Accomplish goal: choose a category of questions	1	4			
Step 3	Accomplish goal: choose an attribute	1	r			
Step 4	Accomplish goal: answer the question	1	r			
Step 5	Accomplish goal: choose "essential" vs. "non-essential"	1	r			
Step 6	Accomplish goal: choose an importance level (if non-essential)	1	r/2			
Step 7	Decide: if no more questions left, then return with sub-goal accomplished. Otherwise, go to step 3	1	r			
Step 8	Decide: if no more categories left, then return with goal accomplished. Otherwise, go to step 2	1	4			
Method for goal – choose the recommendation agent						
Step 1	Decide to choose the agent	1	1	M	1	1
Step 2	Find the agent link	1	1	M	1	1
Step 3	Point to the agent link	1	1	P	1	1
Step 4	Click the agent link	1	1	BB	1	1
Step 5	Return with goal accomplished	1	1			
Method for goal – choose a category of questions						
Step 1	Decide to choose a category	1	1	M	1	4
Step 2	Find the category	1	4	M	1	4
Step 3	Point to the category	1	4	P	1	4
Step 4	Click the category	1	4	BB	1	4
Step 5	Return with goal accomplished	1	4			
Method for goal – choose an attribute						
Step 1	Decide to choose an attribute	1	r	M	1	r
Step 2	Find the question	1	r	M	1	r
Step 3	Point to the question	1	r	P	1	r
Step 4	Click the question	1	r	BB	1	r
Step 5	Return with goal accomplished	1	r			
Method for goal – answer the question						
Step 1	Decide to answer the question	1	r	M	4	r
Step 2	Point to the option	1	r	P	1	r
Step 3	Click the option	1	r	BB	1	r
Step 4	Return with goal accomplished	1	r			
Method for goal – choose "essential" vs "non-essential"						
Step 1	Decide to choose strategy preference	1	r	M	1	r
Step 2	Find the choice	1	r	M	1	r
Step 3	Point to the choice	1	r	P	1	r
Step 4	Click the choice	1	r	BB	1	r
Step 5	Return with goal accomplished	1	r			
Method for goal – choose an importance level (if non-essential)						
Step 1	Decide to choose level	1	r/2	M	1	r/2
Step 2	Point to the level	1	r/2	P	1	r/2
Step 3	Click the level	1	r/2	BB	1	r/2
Step 4	Return with goal accomplished	1	r/2			

Hybrid agents include (31+20.5r) statements, (5+3.5r) P, (5+3.5r) BB, and (10+8.5r) M operators (table A6-4). Hybrid agents have eight, high-level goals to be accomplished: 1) choosing the agent to find a product alternative, 2) choosing categories of questions, 3) choosing attributes they want to express their needs and preferences, 4) answering the questions to express their needs and preferences, 5) deciding whether their

needs and preferences are "essential" or "non-essential", 6) assigning importance weights to those "non-essential" preference-related attributes, 7) deciding whether or not more attributes are to be chosen, and 8) deciding whether or not more categories of questions are available. Users choose to use the agent once, while they repeatedly choose a category of questions and decide whether or not to continue in each category. Also, they need to choose an attribute, answer the question, choose "essential" or "non-essential" preference, and assign importance weights for "non-essential" preferences, and then decide whether or not to continue, for each attribute.

Table A6-5 summarizes the NGOMSL analyses and the estimated execution times for the three types of agents. The results show that Hybrid agents have execution times that are about 15% longer than the AC agents and about 41% longer than the EBA agents.

Table A6-5 Summary of NGOMSL Analyses and Estimated Execution Time			
	AC agent	EBA agent	Hybrid agent
NGOMSL Analyses	(31+17r) statements (5+3r) P (5+3r) BB (10+7r) M	(31+12r) statements (5+2r) P (5+2r) BB (10+6r) M	(31+20.5r) statements (5+3.5r) P (5+3.5r) BB (10+8.5r) M
Estimated execution time (r=11)	175.6s	142.6s	201.8s

APPENDIX 6-3 MEASUREMENT ITEMS

- Perceived Strategy Restrictiveness (PSR)

PSR1: I could select the way this virtual advisor processes my preferences, in generating its recommendations. (r)

PSR2: This virtual advisor allowed me to specify my preferred approach for it to generate its recommendations. (r)

PSR3: I had limited control over the way this virtual advisor makes recommendations.

PSR4: The virtual advisor constrained my alternatives for possible approaches it can use to generate its recommendations.

PSR5: In the context of my preferred way of selecting a digital camera, the approach this virtual advisor uses to generate recommendations was rigid.

PSR6: In the context of my preferred way of selecting a digital camera, this virtual advisor's reasoning processes for generating recommendations were restricted.

- Perceived Agent Transparency (PAT)

PAT1: This virtual advisor made its reasoning process clear to me.

PAT2: It was readily apparent to me how this virtual advisor generates its recommendations.

PAT3: I could not understand how this virtual advisor is performing its job. (r)

PAT4: I could easily understand this virtual advisor's reasoning process.

PAT5: It was easy for me to understand the inner workings of this virtual advisor.

PAT6: I could understand why and how this virtual advisor recommends products to me.

PAT7: This virtual advisor's logic in providing advice was clear to me.

- Perceived Cognitive Effort (PCE)

PCE1: The task of selecting digital cameras using this virtual advisor was very frustrating.

PCE2: Using this virtual advisor, I easily found the information I wanted, to help me decide what to buy. R (dropped)

PCE3: The task of selecting digital cameras using this virtual advisor took too much time.

PCE4: The task of selecting digital cameras using this virtual advisor was easy. R

PCE5: Selecting digital cameras using this virtual advisor required too much effort.

PCE6: The task of selecting digital cameras using this virtual advisor was too complex.

- Perceived Usefulness of Recommendation Agents (PU)

  PU1: Using the virtual advisor can improve my shopping performance.

  PU2: Using the virtual advisor can increase my shopping productivity.

  PU3: Using the virtual advisor can increase my shopping effectiveness.

  PU4: I found using the virtual advisor useful.

- Perceived Ease-of-Use of Recommendation Agents (PEOU)
  PEOU1: Learning to use the recommendation virtual advisor would be easy for me.
  PEOU2: My interaction with the recommendation virtual advisor was clear and understandable.
  PEOU3: It would be easy for me to become skillful at using the recommendation virtual advisor.
  PEOU4: I found using the recommendation virtual advisor easy to use.

- Competence Belief in Recommendation Agents (CPA)

  CPA1: The virtual advisor is competent and effective in providing digital camera recommendations.
  CPA2: The virtual advisor performs its role of giving recommendations very well.
  CPA3: Overall, the virtual advisor is a capable and proficient Internet digital camera recommendation provider.
  CPA4: In general, the virtual advisor is very knowledgeable about digital cameras.

- Benevolence Belief in Recommendation Agent (BNA)

  BNA1: I believe that the virtual advisor would act in my best interest.

  BNA2: If I required help, the virtual advisor would do its best to help me.

  BNA3: The virtual advisor is interested in my well-being, not just its own

- Integrity Belief in Recommendation Agent (ITA)

  ITA1: The virtual advisor is truthful in its dealing with me.

  ITA2: I would characterize the virtual advisor as honest.

  ITA3: The virtual advisor would keep its commitments.

  ITA4: The virtual advisor is sincere and genuine.

- Agent Adoption Intentions (AAI)

  AAI1: Assuming I had access to the system, I intend to use the virtual advisor.

  AAI2: Assuming I had access to the system, I predict I would use the virtual advisor.

  AAI3: Assuming I had access to the system, I plan to use the virtual advisor.

- Disposition to Trust – Competence (DTC)

  DTC1: I believe that most professional people do a very good job at their work.

  DTC2: Most professionals are very knowledgeable in their chose field.

  DTC3: A large majority of professional people are competent in their area of expertise.

- Disposition to Trust – Benevolence (DTB)

  DTB1: In general, people really do care about the well-being of others.

  DTB2: The typical person is sincerely concerned about the problems of others.

  DTB3: Most of the time, people care enough to try to be helpful, rather than just looking out for themselves.

- Disposition to Trust – Integrity (DTI)

  DTI1: In general, most folks keep their promises.

  DTI2: I think people generally try to back up their words with their actions.

  DTI3: Most people are honest in their dealings with others.

- Disposition to Trust – Trusting Stance (DTS)

  DTS1: I usually trust people until they give me a reason not to trust them.

  DTS2: I generally give people the benefit of the doubt when I first meet them.

  DTS3: My typical approach is to trust new acquaintances until they prove I should not trust them.

- Preference for Effort-Saving or Decision Quality (PEQ)

  PEQ1: I am willing to examine the product attributes very carefully in order to make sure that the product fits my preferences perfectly.

  PEQ2: I prefer to shop extensively in order to get exactly what I want.

PEQ3: My time is valuable. As soon as I find a product that is adequate for my needs, I will buy it. (r)

- Product Involvement (PIV)

We would like to know how interested you are in digital cameras. Please use the series of descriptive words listed below to indicate your level of interest in digital cameras:

PIV1: Important	O O O O O O O	Unimportant
PIV2: Irrelevant	O O O O O O O	Relevant (r)
PIV3: Means a lot to me	O O O O O O O	Means nothing to me
PIV4: Unexciting	O O O O O O O	Exciting (r)
PIV5: Dull	O O O O O O O	Neat (r)
PIV6: Matter to me	O O O O O O O	Doesn't matter to me
PIV7: Boring	O O O O O O O	Interesting (r)
PIV8: Fun	O O O O O O O	Not fun
PIV9: Appealing	O O O O O O O	Unappealing
PIV10: Of no concern to me	O O O O O O O	Of concern to me (r)

- Product Knowledge / Expertise – Subjective (PKS)

PKS1: I know pretty much about digital cameras.

PKS2: I do not feel very knowledgeable about digital cameras. R

PKS3: Among my circle of friends, I'm one of the "experts" on digital cameras.

PKS4: Compared to most other people, I know less about digital cameras. R

PKS5: When it comes to digital cameras, I really don't know a lot. R

- Product Knowledge / Expertise – Objective (PKO)

PKO1: When, if ever, is "resolution" important for digital cameras?

PKO2: When, if ever, is "zoom" important for digital cameras?

CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH

7.1 Summary of the Thesis

In online environments, consumers are deluged with an enormous amount of information about products and services from multiple e-vendors. Online recommendation agents provide customers with shopping assistance, but the lack of consumers' trust in recommendation agents prevents the full utilization of their services. However, the nature of trust in online recommendation agents is not well-understood, and few studies have empirically examined the key agent capabilities that can enhance consumers' trust in the agents and their acceptance.

The overall objective of this thesis is to understand user acceptance of online recommendation agents and the formation processes of trust in the agents, and to empirically examine the role of key agent capabilities in facilitating consumers' trust and adoption of the agents.

By integrating TAM with the construct of trust in recommendation agents, the important role of trust in influencing user adoption of the agents is confirmed. Consumers form a certain level of trust in agents that influences their behavioral intentions towards the agents. Trust exerts a direct impact on intentions to adopt recommendation agents as well as an indirect impact via perceived usefulness of the agents.

To understand consumers' trust formation in online recommendation agents and identify the key agent features that stimulate these processes, a written protocol analysis was conducted. Using a prior-research-driven approach, an agent trust formation scheme that included 12 processes was developed to code the written-protocols used by participants to justify their trust levels in recommendation agents. To further examine the predictive power of the major processes identified from the protocol analysis, they were validated via a quantitative analysis. Overall, consumers' expectations, utility assessment, and knowledge about an agent are the most important factors facilitating or inhibiting consumers' trust formation in the agent. Based on these processes, the agent features and capabilities that enhance consumers' trust in a recommendation agent are suggested.

Two agent capabilities are empirically investigated in this thesis: 1) explanation facilities and 2) decision strategy support. Regarding explanation facilities, this thesis empirically tests three types of explanations: *how* explanations, *why* explanations, and *guidance*. The characteristics of online recommendation agents that may hamper consumers' trust-building in the agents are discussed (i.e., agency relationship between agent and users, and high user discretion in agent-user dialogues) and the three types of explanations are suggested to facilitate trust-building by directly dealing with these obstacles. The experimental results confirm that the use of explanations increases consumers' trust in recommendation agents. Furthermore, the differential roles played by the different types of explanations was revealed: the use of *how* explanations increases consumers' beliefs in agent competence and benevolence, the use of *why* explanations increases consumers' beliefs in agent benevolence, and the use of *guidance* increases consumers' beliefs in agent integrity.

The second agent capability investigated is decision strategy support. Hybrid agents are proposed to enhance the decision strategy support by allowing consumer control over agent strategies (i.e., choices of AC and EBA strategies). By supporting both strategies, Hybrid agents not only effectively reduce the number of product alternatives via the EBA strategy, but also retain those alternatives with high quality via the AC strategy. On the other hand, AC agents and EBA agents only support one strategy and consumers do not have control over the strategies employed by the agents. When a consumer's desired decision strategy is not supported by an agent, the agent is perceived to be restrictive and the final recommendations may not fit the consumer's preferences. This research examines the impact of perceived strategy restrictiveness on consumers' trust and perceived usefulness of the agents.

Further, to effectively utilize the decision strategy support capability and make choices in decision strategies, consumers should be able to understand the strategies supported by the agent and know how the agent works (Beaulieu and Jones, 1998; Dhaliwal and Benbasat, 1996). We examined the role of agent transparency. Explanations have been found to increase agent transparency, which leads to trust in the agents, and to help effectively utilize the decision strategy support functionality.

Surprisingly, the impact of decision strategy support is not fully confirmed as expected. In particular, even with explanations provided, the perceived strategy restrictiveness between the Hybrid agents and the AC agents were not significant. One main reason is that the use of decision strategy support requires cognitive effort. This suggests that the extra cognitive effort required by additional agent features should be kept to a minimum. Otherwise, the potential benefits would be limited.

7.2 Contributions

This thesis makes both theoretical and practical contributions. From a theoretical perspective, five major contributions are identified. First, this research tests an integrated Trust-TAM which helps to explain the adoption of online recommendation agents. This research suggests a new perspective for studying IT acceptance. The relational aspects (including trust) are important determinants of behavioral intentions to adopt an online recommendation agent and deserve more research.

Second, this research advances the process theory of trust formation in online recommendation agents. Based on Komiak's (2003) scheme of trust formation in recommendation agents, as well as the process theory of trust in the interpersonal and organizational contexts, a refined scheme with 12 processes is proposed and evaluated with written protocols. The asymmetric structure of trust-building and trust-inhibiting processes is also confirmed. This helps us better understand the trust formation in online recommendation agents.

Third, this thesis empirically tests the impact of explanation facilities on trust in online recommendation agents. The importance of explanations for intelligent systems is well recognized in the IS literature (Dhaliwal and Benbasat, 1996; Gregor and Benbasat, 1999), but empirical testing with validated trust measures has thus far been inadequate. Furthermore, previous studies have produced only generalized conclusions that explanations can help to improve user trust. This study, in contrast, integrates two streams of explanation use research: KBS explanations and DSS *guidance* studies, and

reveals their complementary impact on trust-building. These different types of explanations increase consumer trust via different trusting beliefs.

Fourth, this study empirically investigates an important feature for trustworthy online recommendation agents – agent restrictiveness. In particular, the impact of agent decision strategy support on agent restrictiveness is examined. Perceived agent restrictiveness has been argued to influence user perceptions and evaluations of the agent, but to our knowledge, no prior studies have empirically tested its impact. A new measure for perceived strategy restrictiveness was developed and used to test its impact on consumers' trust and PU of the agents.

Fifth, in addition to perceived agent restrictiveness, the influence of agent transparency and cognitive effort on consumers' trust and the PEOU of agents was empirically tested. Although system transparency has been generally discussed in the IS literature (Gregor and Benbasat, 1999; Silver, 1991a), empirical examination of its impact and antecedents is lacking. More importantly, together with perceived strategy restrictiveness, the relative impact of these variables on the important antecedents in Trust-TAM was evaluated. As suggested by Davis (1989), it is important to identify factors that influence the antecedents of user acceptance of a technology. This study contributes to research by identifying these factors.

This thesis also makes significant contributions to practice. The results of this thesis have several implications for the design of trustworthy online recommendation agents. First, the importance of trust, in determining user acceptance of recommendation agents, calls attention to the agent features that can induce trust-building processes and prevent trust-inhibiting processes. For example, expectation confirmation processes require designers to understand and confirm user expectations. Several solutions were suggested in chapter 4, such as personalized agent-user dialogues.

Second, this research offers an effective approach to store knowledge in online recommendation agents. The three types of explanations explored in chapter 3 help to facilitate the flow of knowledge from recommendation agents to their users, while improving the way in which consumers convey their needs and preferences to the agents.

With adequate and appropriate knowledge embedded within them, recommendation agents can be an effective way for companies to provide electronic customer services to facilitate online consumer decision-making.

Third, by considering both the benefits and the costs of the reduced agent restrictiveness for consumers, this study provides practical guidelines for the design of decision strategy support provided by recommendation agents. Effective user control and additional agent features require that: 1) a set of appropriate explanations be provided so that users can understand these features and employ them properly, and 2) using these features should not induce much cognitive effort so that users are willing to use them. A transparent agent with additional features that empowers user control but does not require much additional effort, delivers more benefits to users (e.g., more useful and trustworthy) and provides more effective recommendation services and gains a higher chance of user adoption.

7.3 Future Research

As discussed in previous chapters, important future research areas are summarized as follows. First, more research is needed to examine other possible explanations for online recommendation agents. As mentioned in chapter 3, other important explanations have been put forward, e.g., terminological explanations and justifications for reasoning processes (Gregor and Benbasat, 1999), that are not addressed in this study. They may further enhance consumers' trust in agents and deserve attention in future research.

Second, this research identified several trust formation mechanisms that have been largely ignored in the literature, such as expectation confirmation and utility assessment. Future research is warranted to examine key agent features that might influence these processes, to facilitate consumers' trust in recommendation agents.

A third research area is to investigate other methods that influence agent restrictiveness. Other types of restrictiveness were proposed by Silver (1990), such as

communication restrictiveness related to the set of questions and its sequence in the agent-user dialogues. It is worthwhile to also explore the optimum level of agent restrictiveness. As pointed out by Silver (1990), with too little restrictiveness, users might be overloaded in making choices, while with excessive restrictiveness, the decision processes of users are not well supported.

In conclusion, consumer trust in online recommendation agents has emerged as an important issue in electronic environments. Recommendation agents need to be transparent to users by providing a set of appropriate explanations, and to provide high decision strategy support to effectively narrow down the product alternatives, while retaining those products that are most suitable for consumers. Further, the additional features should not require much cognitive effort so that users will be willing to employ them. Incorporating agent features that can facilitate consumers' trust in an agent encourages their acceptance of the agent, thereby strengthening users' intentions to transact with the Web vendors.

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