ABSTRACT

Title of Dissertation: THE VALUE OF IT-ENABLED RETAILER
                         LEARNING: CAN PERSONALIZED PRODUCT
                         RECOMMENDATIONS (PPRS) IMPROVE CUSTOMER
                         STORE LOYALTY IN ELECTRONIC MARKETS?

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Dissertation directed by: Professor Ritu Agarwal and Professor Hank Lucas
                            Department of Decision and Information Technologies

Personalization is a strategy that has been widely adopted by online retailers to enhance their customers' shopping experience, with the ultimate goal of building a strong and enduring customer relationship. Personalized product recommendations (PPRs) are product recommendations adapted to individual customers' preferences and taste. So far, very few empirical studies have ever investigated the impact of PPRs from a consumer behavior perspective. Whether PPRs generate any value for consumers and ultimately, retailers, is still an open question.

To fill this gap in the literature, in this study, drawing upon the household production function model in the consumer economics literature, I develop a theoretical framework that explains the mechanism through which PPRs influence customer store loyalty in electronic markets. Online shopping can be viewed as a household production process and customer store loyalty is driven by shopping efficiency. Building upon retailer learning, higher quality PPRs can increase consumers' online product brokering

efficiency, which in turn increases their repurchase intention. A two-phase lab experiment was conducted among 253 undergraduate students in the business school. The subjects completed a simulated purchase at Amazon.com and the quality of PPRs they received was manipulated. Empirical analyses indicate that higher quality PPRs improve consumers' online product brokering quality, which in turn increases their repurchase intention. Consumers make higher quality purchase decisions and experience more fun during the online product brokering process. A surprising finding is that higher quality PPRs increase consumer online product brokering cost. Consumers spend more time on decision making and have more difficulty reaching a purchase decision. Implications, limitations, and contributions of this study are discussed and areas for future research are suggested.

THE VALUE OF IT-ENABLED RETAILER LEARNING: CAN PERSONALIZED
PRODUCT RECOMMENDATIONS (PPRS) IMPROVE CUSTOMER STORE
LOYALTY IN ELECTRONIC MARKETS?

by

Tongxiao Zhang

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Advisory Committee:

       Professor Ritu Agarwal, Co-Chair
       Professor Hank Lucas, Co-Chair
       Professor Roger Betancourt
       Assistant Professor Sanjay Gosain
       Professor Brian Ratchford

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CHAPTER ONE – INTRODUCTION

Online startups face significant customer acquisition cost, which can only be recouped from the repeat purchases of their loyal customers. To take advantage of the greater economies of scale in the electronic channel, it is crucial for online retailers to build a large loyal customer base. In the early days of e-commerce, it was widely believed that building customer store loyalty was more challenging for online retailers who normally sell commodity products, due to lower consumer information search cost and switching cost in electronic markets. However, more recent studies present a completely different picture: consumers demonstrate strong store loyalty online. An understanding about the two different roles information technology has played in electronic markets may help us solve this paradox. Advances in information technologies on one hand have reduced consumer information search cost and switching cost, but on the other hand, have provided online retailers with more powerful tools to retain their customers.

Although personalization, an IT-enabled strategy, has been widely adopted by online retailers in hopes of building a strong and enduring customer relationship, no empirical studies have examined this phenomenon from a consumer behavior perspective. Whether personalization has generated any value to online customers and retailers is an important but unanswered question. This study is one of the first attempts to address this gap in the e-commerce literature.

In this chapter, first, I give an introduction about the background of this study – customer store loyalty online. Next, I argue how PPRs, one important form of

personalized service offered by online retailers, have the potential to improve customer

retention online. Finally, I point out the gap in the existing literature and discuss the

purpose of the study.

1.1 Customer Retention online

Since the dot.com bubble burst in 2000, many observers expected B2C e-tailing to

suffer a similar fate. To the contrary, retail Internet sales have made surprisingly strong

and consistent progress in subsequent years, with annual growth in the double digits.

According to the most recent report released by the Commerce Department, retail e-

commerce sales rose sharply in the fourth quarter of 2003, as consumers spent $17.2

billion online, up 25% from the fourth quarter of 2002. E-commerce sales accounted for

1.9% of total retail sales in the fourth quarter, up from 1.6% in the year-ago quarter. For

all of 2003, online sales were $55 billion, up 26% from 2002 (Marlin 2004). eMarketer

predicts that U.S. online retail sales will continue to grow rapidly – from $45.5 billion in

2002 to $88 billion in 2005, almost double in three years (McIntosh 2003).

1.1.1 Importance of Customer Retention to Online Retailers

The Internet has now become an important channel for marketing and distribution

of products and services. High initial investments and low marginal cost suggest that

online retailers need to build a large customer base to truly leverage the efficiency of this

channel. Although new consumers are entering the electronic market every year, this

growth is being outpaced by the growth in new websites (Hanson 2000). It can be

expected that the battle for visitors will soon shift from the current emphasis on attracting

new users to retaining existing ones (Hanson 2000; Peppers and Rogers 1997).

Customer acquisition cost is the largest component of cost incurred by B2C startups and represents a substantial portion of the initial financial losses these firms typically experience. According to McVey (2000), customer acquisition cost is estimated to range from $40 per customer for Amazon.com to over $400 for some online brokers. Such high customer acquisition cost can only be recouped from a long-term stream of profits generated by repeat purchases of loyal customers. It has been found that in traditional markets, increasing customer retention by as little as 5% can result in a long-run profit increase of between 25% and 95% across various industries (Reichheld and Sasser Jr. 1990). Due to greater positive economies of scale associated with the Internet channel, this number could arguably be even higher for online retailers. Therefore, the ability to build customer store loyalty is a major driver of success for retailers in electronic markets.

1.1.2 Paradox of Online Customer Store Loyalty

In the early days of e-commerce, it was widely believed that building customer store loyalty online is more challenging than offline. Except a few private brand products, retailers are mainly offering standardized or commodity products, which are valued equally by consumers regardless of the provider, and therefore, to consumers, price could be the only factor that differentiates one retailer from another. In traditional markets, retailers can survive by charging a price premium because of consumers' high information search cost and switching cost. The Internet has significantly lowered consumers' information search cost and switching cost and consumers now could easily find and switch to whichever retailer who offers the lowest price. As a result, the

expectation was that Bertrand competition among online retailers would ensue, with the prices charged for commodity products converging to the marginal cost in equilibrium.

However, this is not what is really happening. Recent studies have consistently found that price dispersion still exists in several commodity product markets (e.g., Bailey, Yao, and Faraj 1999; Brown and Goolsbee 2002; Brynjolfsson and Smith 2000a; Ellison and Ellison 2001; Pan, Ratchford, and Shankar 2002). One of the major reasons that online retailers charging higher prices can survive is because consumers are not searching and switching as much as predicted. In other words, consumers demonstrate strong store loyalty online. It has been found that online shoppers, even those Internet Shopbot users who are supposed to be more price sensitive than general consumers, normally engage in very limited comparison shopping. They either go directly to an online store or compare at most two to three different stores before making their purchase decisions (Brynjolfsson and Smith 2000b). Consistently, recent studies have found that the electronic market is actually more concentrated than the traditional market. Across many product categories, a few online firms are dominating the market and are enjoying a price premium (Brynjolfsson and Smith 2000a; Latcovich and Smith 2001). According to research by Web21, the top four Internet book retailers (Amazon.com, Barnes&Nobel.com, Borders.com, and Buy.com) account for 99.8 percent of all hits for online book retailers (Latcovich and Smith 2001). Moreover, the big three book retailers have a $1.72 price advantage over generic retailers. Amazon.com has a $2.49 price advantage over generic retailers and about a $1.30 price advantage over its two closest rivals, Barnes and Noble, and Borders (Smith and Brynjolfsson 2001).

1.1.3 Why Customer Store Loyalty Exists Online

Why are online retailers still able to retain their customers when consumer information search cost and switching cost are trivial compared to those offline? This question can be answered from two perspectives. From consumers' perspective, even though information search cost and switching cost online are lower than those in the traditional market, they are not trivial. Smith (2002) points out that consumers need two types of information when shopping online – product information and service information. Although the availability of Internet Shopbots has significantly reduced consumers' search cost for product information, consumers' search cost for service information is still as high as that in the traditional market. In addition, although transportation cost is not a factor anymore online when alternative stores are just a click-away, consumers may incur significant cognitive and time cost to familiarize themselves with the website interface when switching to a store they have not visited before.

From retailers' perspective, although the products they are offering are homogeneous, the services are not. It is the service differentiation that has ultimately saved online retailers from pure price competition. Retailers who offer superior services are able to charge a higher price without losing their customers. Advances in information technologies have given online retailers the opportunity to improve customer retention by providing their customers with a variety of value-added services. Personalization, a strategy enabled by cutting-edge information technologies, has been widely adopted by online retailers to enhance their customers' shopping experience in hopes of building a strong and enduring customer relationship. Retailers can choose to personalize various aspects of their services and the focus of this study is on one such service – information personalization.

1.2 Information Personalization

Although retailers are able to offer a larger variety of products and a greater amount of information to their customers online than they could do offline, they may not necessarily generate more value for their customers if consumers' information search and processing cost online are just as high as they are offline. The wide implementation of search engines at online retailers' websites has significantly reduced consumers' information search cost – the time and cognitive cost to locate and retrieve relevant information, however, consumers are still facing significant information processing cost when making purchase decisions. Information overload or choice overload has been cited as the reason that online consumers tend to perform very limited pre-purchase information search, which may lead to suboptimal purchase decisions (Alba and Hutchinson 2000; Haubl and Trifts 2000).

Information personalization, or adapting product information to individual consumer's needs, is an important step in the direction of alleviating consumers' information overload. The ultimate goal of information personalization is to present the product information that individual consumers want to see in the appropriate manner and at the appropriate time (Pierrakos, Paliouras, Papatheodorou, and Spyropoulos 2003). The interactivity of the Internet channel and the development of database technology have made it much more efficient for online retailers to collect, store, and analyze a huge amount of data on individual customers' needs and preferences. This enables each firm to customize product information for individual customers at a relatively low cost, thus makes mass customization and one-to-one marketing a reality in electronic markets.

Offering real-time personalized product recommendations (PPRs) is one important form of information personalization that has been implemented by online retailers. Collaborative filtering – the most popular technology used by a class of information personalization systems called recommender systems – looks at individual consumer's behavior data, such as purchase history and stated preferences, to predict the future behavior of like-minded people.

By offering PPRs, online retailers are engaged in a learning relationship with their customers, which is an ongoing connection that becomes smarter over time as the two interact with each other, collaborating to meet the customer's needs. In this relationship, individual customers teach the company about their preferences and needs, which may give the company an immense competitive advantage. The more customers teach the company, the better it becomes at providing exactly what they want, and exactly how they want it. This capability is difficult for its competitors to imitate because it takes time for consumers to teach its competitors to do the same. In other words, "retailers' knowledge base regarding their customers is continuously enhanced, lessening the customer' incentive to defect to another seller who has to build such knowledge from scratch" (Srinivasan, Anderson, and Ponnavolu 2002).

However, whether PPRs have generated any value for consumers and retailers is still an open question. On one hand, some anecdotal evidence has demonstrated that PPRs can significantly improve customer store loyalty. For example, as one of the pioneers in implementing personalized recommendations on its website, Amazon.com has established a large loyal customer base. Sixty three percent of its customers are repeat buyers, compared to 35 percent to 40 percent of a typical e-commerce site (Lach

1998). On the other hand, a report released by Jupiter Research on October 14, 2003 revealed a surprising finding: most sites that have deployed personalization have realized inadequate returns on their investments. Only 14% of surveyed consumers say that personalized offers or recommendations on shopping Web sites lead them to buy more often from online stores, and just 8% believe that personalization increases their repeat visits to content, news or entertainment Web sites. This is in contrast to the majority of consumers who stated that basic site improvements would make them buy or visit Web sites more often – 54% cited faster-loading pages and 52% cited better navigation as greater incentives. The contradictory evidence given by the literature implies that implementing personalization may not necessarily bring benefits to online customers and ultimately, retailers.

According to Jupiter Research (2003), building and operating a personalized Web site costs four or more times more than operating a comparable dynamic site. Therefore, whether personalization in general and PPRs in particular have delivered adequate return to online retailers is a critical issue that needs to be systematically investigated.

1.3 Purpose of the Study

The purpose of this study is to answer the following two important questions about PPRs: (1) Do PPRs generate any value to online consumers and retailers? If so, how is the value generated? And (2) compared to other aspects of retailers' services, how important are PPRs in building customer store loyalty online?

Drawing upon the household production function model and human capital model rooted in the consumer economics literature, in this study, I develop and empirically test

a framework that explains the mechanisms through which PPRs influence customer store loyalty in electronic markets. Online shopping can be viewed as a household production process and customer store loyalty is driven by shopping efficiency. Building upon retailer learning, higher quality PPRs can increase consumers' online product brokering efficiency, which in turn increases their repurchase intention. A two-phase lab experiment was conducted among 253 undergraduate students in the business school. The subjects completed a simulated purchase at Amazon.com and the quality of PPRs they received was manipulated.

Empirical analyses indicate that higher quality PPRs improve consumers' online product brokering quality, which in turn increases their repurchase intention. Consumers make higher quality purchase decisions and experience more fun during the online product brokering process. A surprising finding is that higher quality PPRs increase consumer online product brokering cost. Consumers spend more time on decision making and have more difficulty reaching a purchase decision.

This study makes the following contributions to the literature: First, complementing previous studies using analytical modeling approach, this study develops a theoretical framework that explains the strategic value of personalization in general and PPRs in particular from a consumer behavior perspective. Second, this study provides a new perspective to understand customer store loyalty, that is, customer store loyalty is driven by shopping efficiency. Online shopping demands sufficient cognitive effort from consumers, and therefore, cognitive efficiency of the shopping process is what drives customer store loyalty. Third, this study emphasizes the role of learning in improving consumers' cognitive efficiency when shopping online. Consumer learning and retailer

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learning, which is enabled by information technologies such as recommender systems, jointly contribute to consumers' online shopping efficiency and this relationship is strengthened over time. Fourth, this study systematically examines the impact of consumer store/website knowledge on consumer online shopping efficiency and store loyalty. Although consumer product category knowledge has received extensive attention from the literature, how consumer store/website knowledge – another type of knowledge accumulated by consumers through a learning process – influences consumer shopping behavior has long been ignored. Finally, this study provides a new data collection approach for future research on PPRs. By integrating a survey with a lab experiment, the study design creates a natural setting for the subjects to complete a purchase task and at the same time, makes it possible for researchers to perform some manipulation.

In addition, findings of this study provide important guidance for online retailers to better adjust their customer retention strategy and reap more value out of cutting edge information technologies. Personalization is a powerful customer retention weapon and is uniquely available to retailers in electronic markets. However, to improve the returns on the huge investment in personalization technologies, online retailers need to provide more incentive to their customers to get them more involved in the joint learning process.

The rest of the dissertation is structured as follows. Chapter Two reviews existing literature in related areas and proposes a conceptual model that explains how personalized services offered by online retailers influence customer store loyalty. Next, building upon this conceptual model, Chapter Three develops a research model to investigate the impact of PPRs on customer store loyalty. Then, Chapter Four describes

the methodology that was used to empirically test the model and reported the results of three rounds of pilot studies. Finally, Chapter Five reports the results of final data analyses discusses the implications, contributions, and limitations of this study and suggests directions for future research.

CHAPTER TWO - LITERATURE REVIEW

In this chapter, I first review previous research in related areas. Then, based on the literature review, I develop a conceptual model that explains how personalized services offered by online retailers affect consumers' online shopping efficiency, and ultimately, their store loyalty.

Previous literature is reviewed in the following order: (1) personalization and recommender systems; (2) customer loyalty; (3) household production function and human capital framework; (4) consumer learning; and (5) retailer learning. The overview of the literature review is presented in Figure 1. The review of previous research on personalization and recommender systems reveals that very few empirical studies have ever investigated the strategic value of personalization from a consumer behavior perspective. To develop a theoretical framework to guide this empirical study, existing literature about customer loyalty is discussed. Due to the limitations of the customer satisfaction – store loyalty framework, in this study, I adopt an alternative perspective to examine customer store loyalty online. Drawing upon household production function and human capital model in the consumer economics literature, I argue that consumers' store loyalty is mainly driven by their online shopping efficiency, which in turn is jointly affected by consumers' product category knowledge and website knowledge accumulated through consumer learning, and the quality of personalized services provided by online retailers building upon retailer learning.

[Insert Figure 1 Here]

2.1 Personalization and Recommender Systems

A recommender system is a tool for online retailers to implement personalization. PPRs generated by recommender systems can be used by online retailers to offer more targeted product information to their customers. A review of previous studies on personalization help us better understand the role of recommender systems in online retailers' personalization strategies.

2.1.1 Various Forms of Personalization

Personalization is now a popular marketing tool adopted by more and more online retailers to reap the value of efficient retailer learning enabled by information technologies. "Personalization" is defined as the design, management, and delivery of content and business processes to users, based on known, observed, and predictive information (Meister, Shin, and Andrews 2002). Personalization technologies enable a retailer to leverage customers' previous buying habits and customer profile information to make automatic decisions about what data to display to the user, and how to display it. Personalization has been implemented by online retailers in many different ways: (1) customized Web pages - retailers allow customers to develop their own web or home pages; (2) targeted information – retailers actively target information to customers, such as targeted advertising, promotions and tailor-made activities; (3) customer-retailer interaction – retailers involve customers directly by asking for feedback, points of view on products, comments or suggestions on a range of topics and then sending an automated "thank you" and/or follow up with a personalized response; (4) customer-to-customer interaction directly or indirectly – retailers use the input from some customers to generate product reviews for the benefit of other customers, or establish online

communities on their website to bring like-minded customers together for discussions or chats; (5) customized products – retailers are increasingly customizing products and offering this on a mass-market at an acceptable price to the customer (e.g., Dell.com's configuration tool); and (6) rewards and incentives – retailers develop frequent purchaser programs to reward those loyal customers with a personalized price or other offers.

2.1.2 Previous Studies on Personalization

Murthi and Sarkar (2003) provide a comprehensive review of previous studies on personalization. They classify previous research into two streams: (1) personalization process, and (2) personalization and firm strategy.

The first stream of research focuses on the technical issues associated with personalization, the personalization process. Previous studies in this stream have examined various mechanisms to collect consumer data, various techniques that can be used for analyzing and predicting consumers' preferences, and various methods to generate PPRs to consumers. In studies on personalization and firm strategy, game theory is the dominant paradigm. Previous studies in this stream have investigated the following issues: the impact of personalized pricing on firms under competition, personalization and consumers' privacy concerns, personalization and product differentiation, the impact of the timing of adopting personalization on firms' performance, personalization with price discrimination, and personalization and bundling. The general conclusion drawn from all the studies in this stream is that although the reduction in consumers' information search cost leads to an increase in consumers' power relative to the firm, effective personalization strategies can help shift

the power back in favor of the firm. Additional details are available in Murthi and Sarkar's (2003) paper.

The current study falls into the second stream. As pointed out by Murthi and Sarkar (2003), as all of the studies in this stream have an adopted analytical modeling approach, to reach a better understanding about the strategic value of personalization to firms, empirical research is needed to validate the assumptions and the results of the analytical models. In this study, I focus on one form of personalization – information personalization, more specifically, personalized product recommendations (PPRs).

2.1.3 Personalized Product Recommendations (PPRs)

In order to understand why PPRs are valuable to online consumers, it is first necessary to characterize the consumer's consumption process.

Consumer Consumption Stages

In the consumer behavior literature, consumption is defined as "the actions and decisions involved in buying and using goods and services" (Nicosia 1966) and is viewed as being comprised of multiple stages (Engel and Blackwell 1973; Howard and Sheth 1969; Maes, Guttman, and Moukas 1999; Nicosia 1966). The typical stages in a consumption process are: (1) Need identification. At this stage, consumers become aware of unmet needs. (2) Product brokering. Here, consumers gather product information from various sources and evaluate all alternatives to determine what product to buy. (3) Merchant brokering. At this stage, consumers acquire information about merchants who are selling products in their consideration set and determine who to buy from. This stage includes the evaluation of merchant alternatives based on consumer-

selected criteria, such as price, warranty, availability, delivery time, reputation, etc. (4)

Negotiation. Consumers negotiate with the merchant to determine the terms of the

transaction. In traditional retail markets, prices and other aspects of the transaction are

often fixed leaving no room for negotiation. In other markets, such as stocks, automobile

fine art, local market, etc., the negotiation of price and other aspects of the deal are

integral to product and merchant brokering. (5) Purchase and delivery. At this stage,

consumers acquire the product and make the payment, and (6) Post-sale service.

Consumers receive support from the merchant if the product does not function properly.

In the consumption process, product brokering is the stage that requires

consumers to search and process a large amount of product information and information

overload may prevent consumers from reaching an informed purchase decision

Information Overload

As an efficient communication and distribution medium, the Internet enables

online retailers to offer their customers with almost unlimited variety of products and

large amounts of product information. However, with limited time and cognitive

capacity, going through so much information and choosing among so many options is a

daunting task to most customers.

About two decades ago, Jacoby and his associates (1974; 1975) reported the

results of two experiments designed to ascertain the influence of the amount of

information available to a consumer on his/her ability to make a correct choice among

food products. They found that too much information can be overwhelming to

consumers and lead to suboptimal purchase decisions. This work established the existence of information overload in the consumer behavior literature.

Consumers engage in online shopping incur two types of cost before making their purchase decisions, information search cost and information processing cost. Information search cost is the cost to locate and retrieve relevant information from the Internet, while information processing cost is the cost to examine and analyze the available information to make a judgment. Wan, Menon and Ramaprasad (2003) point out that consumer product brokering can be classified into two categories, search-dominated vs. processing-dominated. In traditional markets, information search cost is linearly correlated with the number of alternatives included in consumers' choice set, while in electronic markets, information search cost is approximately fixed regardless of the number of alternatives, in large part due to various search tools available to online consumers. Although in the online setting consumers' information search cost has been significantly reduced, consumers' information processing cost is still as high as those in the traditional markets. As West and colleagues (1999) have observed, whereas Moore's law has reduced the cost of computing, it has not affected the cost or speed of the human information processor. To some extent, we can say that consumers' product brokering process is search-dominated in traditional markets but is processing-dominated in electronic markets. The ease of retrieving information online does not necessarily increase consumers' product brokering efficiency. With too many alternatives to evaluate, consumers are now facing "choice overload" (Wan, Menon, and Ramaprasad 2003).

To alleviate consumer choice overload, online retailers are taking advantage of various cutting-edge information technology innovations to provide personalized product

information on their website in order to reduce the total number of alternatives customers have to evaluate before finding the products that really meet their needs. Recommender systems are one of the most widely implemented information technology innovations at online retail stores.

2.1.4 Recommender Systems

Recommender systems have been deployed on many websites to provide PPRs to millions of online consumers (Sarwar, Karypis, Konstan, and Riedl 2000). Online retailers invest in learning about their customers by collecting and analyzing customer data, then, use recommender systems to operationalize that learning, and present information that better matches consumer needs.

A recommender system is comprised of an ever-increasing database of user preference information, a friendly Web interface that induces consumer cooperation, and a recommendation engine (Sarwar et al. 2000). Various techniques have been used by recommender systems to generate recommendations. In general, these techniques can be classified into two categories: (1) content-based filtering; and (2) collaborative filtering (Ansari, Essegaier, and Kohli 2000; Ariely, Lynch, and Aparicio IV 2004). Content-based filtering makes recommendations on the basis of consumer preferences for product attributes. The consumer's rating of an unknown product is predicted by relating the consumer' reactions to other products in the database on a set of attribute dimension scores. In contrast, the collaborative filtering approach mimics word-of-mouth recommendations. These methods predict a consumer's preferences as a linear, weighted combination of other consumers' preferences. In general, this approach uses the

reactions of other consumers within the database, and their similarity to the target

consumer (Goldberg, Nichols, Old, and Terry 1992).

Typology of Recommender Systems

With a large variety of recommender systems implemented by online firms,

Schafer, Konstan, and Riedl (1999) propose a framework to categorize recommender

systems along two dimensions: the degree of automation and the level of persistence of

the recommendations.

The degree of automation ranges from completely automatic recommendations to

completely manual recommendations based on the amount of customers' effort required

to access recommendations. Completely automatic recommender systems generate

recommendations without explicit effort by the customer. The customer simply interacts

with the site as he or she wishes, and suddenly a recommendation appears that is

appropriate for the customer's interests. In contrast, when using completely manual

recommender systems, the customer needs to take explicit effort to specify his/her

preferences and request for recommendations. Recommender systems can have the

following different degrees of automation: (1) customers receive recommendations

through the course of normal navigation, and recommendations appear as part of the item

information page; (2) customers only need to request recommendations; (3) customers

need to choose from predefined criteria/options to generate recommendations; and (4)

customers need to type in keywords in free form to receive recommendations.

The level of persistence ranges from completely ephemeral recommendations to

persistent recommendations. Ephemeral recommendations are made during the course of

a single customer session, and are not based on any information from previous sessions of this customer. Persistent recommendations are predicted on the site recognizing the customer, and suggesting products to the customer based on the customer's preferences revealed in previous sessions.

Target Recommender Systems

The current study focuses on recommender systems that require no explicit effort or instructions from customers and offer persistent recommendations. This choice was made for two reasons: first, only persistent recommendations are built upon IT-enabled retailer learning. Although retailer learning has never been formally defined in the literature, the definition of consumer learning (e.g., Gregan-Paxton and John 1997; Hutchinson and Alba 1991) implies that learning is a process where performance improves over time. As more information is collected and analyzed or learned about each individual customer, the recommendations generated by persistent recommender systems become more accurate and relevant. Ephemeral recommendations do not have this nature as they are generated based only on customers' browsing patterns in the current session. Persistent recommendations building upon retailer learning have the potential for more strategic impact on retailers. Theoretically, only persistent recommender systems can really bring sustained competitive advantage to retailers as consumers' purchase history cannot be transferred to other websites when consumers switch. It is the accumulated knowledge about individual consumers that can effectively prevent its competitors from easily imitating this strategy.

Second, according to Nunes and Kambil (2001), strictly speaking, only recommendations generated by recommender systems that do not need explicit effort from customers can be classified as real personalization. They argue that conceptually, personalization and customization are different. Customization needs a customer to specify his or her own preferences, such as the My Yahoo! Feature at Yahoo.com. By contrast, personalization does not rely on explicit user instructions as it uses artificial intelligence to find patterns in customers' choices or demographics and to extrapolate from them (Nunes and Kambil 2001).

Improving customer retention has been cited as one of the major motivations underlying online retailers' decision to implement recommender systems and offer PPRs to their customers. A review of previous studies on customer loyalty will help us better understand the role of PPRs in customer retention online.

2.2 Customer Loyalty

Customer loyalty is a topic that has received much attention in the consumer behavior literature. Two types of customer loyalty are identified in the retail context – customer brand loyalty and customer store loyalty. They are two different but closely related concepts.

2.2.1 Customer Brand loyalty

Customer brand loyalty is defined as a "deeply held commitment to re-buy or re-patronize a preferred product consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior"(Oliver, 1997, p. 392). Brand loyalty

has two dimensions, behavioral or purchase loyalty, and attitudinal loyalty. Behavioral

loyalty refers to repeated purchases of a brand, while attitudinal loyalty is reflected in the

degree of dispositional commitment in terms of some unique value associated with a

brand. Correspondingly, there are two approaches to measure brand loyalty, the

behavioral measure, or actual purchases, and cognitive measure, or beliefs and attitudes

towards a brand (Holland and Baker 2001). Using the two-dimensional framework of

brand loyalty, Dick and Basu (1994) propose a typology of brand loyalty comprising of

four cells: (1) no loyalty – low attitude combined with low repeat patronage; (2) spurious

loyalty – low attitude but high repeat patronage; (3) latent loyalty – high attitude but low

repeat patronage; and finally, (4) true loyalty – high attitude together with high repeat

patronage.

2.2.2 Customer Store Loyalty

Building upon previous literature on customer brand loyalty, researchers have

extended this concept to explain consumers' loyalty to service providers, or store loyalty.

Adapting Oliver's (1997) definition of brand loyalty to this context, customer store

loyalty here is defined as a deeply held commitment to re-patronize a retail store

consistently in the future despite situational influences and marketing efforts that may

have potential to cause switching behavior. In the current study, I focus on the

behavioral dimension of customer store loyalty, i.e., customers' repeat patronage of a

retail store, which includes both the spurious loyalty and true loyalty defined in the

typology proposed by Dick and Basu (1994). Although true loyalty should be the

ultimate goal pursued by all firms, spurious loyalty has value to firms too, at least in the

short-run since retailers benefit from all consumers' purchases regardless of the underlying drivers of their purchase behavior.

Customer Satisfaction – Store Loyalty Framework

In the literature of service marketing, the dominant theoretical framework to study customer store loyalty is the service quality – customer satisfaction – customer store loyalty model. In this model, it is argued that retailers' service quality influences the level of customer satisfaction, which in turn determines customers' future purchase decisions (e.g., Cronin and Taylor 1992; Taylor and Baker 1994).

A major implication of this framework is that the more satisfied a customer is, the more loyal he/she will be. However, although numerous studies have been conducted to test this framework (e.g., Cronin, Brady, and Hult 2000), the findings are not consistent and sometimes even contradictory. This framework demonstrates strong explanatory power in some studies, but fails to explain customer store loyalty under many other circumstances. Anderson and Sullivan (1993) find the t-values for the satisfaction-repurchase intention relationship range from 1.1 to 13.1 across several product categories. They argue that such high variability suggests the possibility that there are some other factors driving customer store loyalty. At the same time, as companies devote more resources to satisfying the customer and to tracking customer satisfaction, they fail to find a direct relationship between customer satisfaction and organizational profits (Anderson, Fornell, and Lehmann 1994; Jones and Sasser Jr. 1995; Oliver 1999; Reichheld 1996). It has been observed that satisfied customers, even highly satisfied ones, often switch

suppliers, and the relationship between stated satisfaction and repeat purchase ranges from very weak to non-existent in many cases (Neal 1999).

Although this satisfaction-loyalty framework is still widely adopted by studies in this area, the limitations of this framework indicate that alternative frameworks are still needed for us to have a richer understanding of customer store loyalty.

2.3 Customer Value

Some researchers have argued that the true mediating variable between service quality and customer store loyalty is customer value (Dodds, Monroe, and Grewal 1991; Parasuraman and Grewal 2000). Even satisfied customers are unlikely to patronize a business if they feel that they are not getting the best value for their money. Instead, they will seek out other sellers in an ongoing effort to find better value. This view of customers as value seekers also sheds light on the paradox of why dissatisfied consumers are still loyal. According to the literature, dissatisfied consumers can be loyal (spurious loyalty) because of high switching cost. When facing high switching cost, although consumers are not satisfied with their current service provider, they get the best value by continuing to consume the same services. Compared to the service quality–customer satisfaction–customer store loyalty framework, I argue that the service quality-customer value-customer store loyalty framework is more powerful as it can be applied to more general settings to explain consumer loyalty, where the traditional framework fails.

2.3.1 Typology of Customer Value

According to Holbrook (1996), customer value can be categorized along two dimensions, extrinsic value versus intrinsic value, and active versus reactive value.

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Extrinsic value refers to a "means-ends relationship wherein some thing or event (a product or consumption experience) is a means instrumental in accomplishing some further purpose". Intrinsic value pertains to an "experience appreciated for its own sake, apart from any other consequences that may result therefrom" (Holbrook 1996). In the context of retail, extrinsic value is typically derived from shopping trips that are utilitarian in nature. Shopping is regarded as an errand and work. By contrast, intrinsic value results from the fun and playfulness of an experience, rather than from task completion (Babin and Darden 1994). Active value pertains to a customer's desire for the efficient use of resources or for receiving functional or emotional benefits. Reactive value, on the other hand, is obtained when a customer responds positively to products, service, or environment that satisfies his or her needs while shopping. Building upon the two-dimension framework, Holbrook (1996) proposes a typology of customer value in the context of shopping at retail stores: efficiency, excellence, play, and aesthetics.

2.3.2 Customer Value of Online Shopping

As in the offline retail environment, it has been suggested that consumers seek different types of value when shopping online. According to Wolfinbarger and Gilly (2003), there are two groups of consumers in electronic markets, experiential shoppers and goal directed shoppers. Experiential shoppers have an ongoing, hobby-type interest in shopping, just like collectors and hobbyists enjoying the thrill of the hunt as much as the acquisition of items for collection. For such customers, play and aesthetics may be more important than efficiency and excellence. By contrast, goal-oriented or utilitarian shopping has been characterized as task-oriented, efficient, rational, and deliberate. Goal-oriented shoppers desire to purchase what they want quickly and complete a

transaction without distraction. Shopping is more like work rather than fun, and thus, efficiency may be the most important value perceived by goal-oriented customers.

A recent study by Jupiter Research (2003) found that two-thirds to four-fifths of Internet buyers engage in narrowly defined searches for specific products online. In an online survey among 1013 consumers, 71% of shoppers said their most recent online purchase had been previously planned, while 29% said they had been browsing when they made their purchase. Clickstream analysis of major e-commerce sites also suggests that online consumers tend to be goal-focused. It has been found that the length of visit at top sites is largely 15 minutes or less, just about long enough to find a product and actually complete the transaction (Wolfinbarger and Gilly 2001). Consistently, Szymanski and Hise (2000) find that convenience is perceived as one of the major benefits of shopping over the Internet.

In summary, online shoppers are more likely to be goal-oriented rather than experiential. This implies that in the context of online shopping, efficiency may arguably be the most important value that consumers are seeking.

2.4 Human Capital Model and Household Production Function

The integration of the human capital model (e.g., Becker, Grossman, and Murphy 1994) and the household production model in the consumer economics literature provides a theoretical framework for us to understand why efficiency drives customer store loyalty.

Many of us may have observed the following consumer behaviors: consumer brand loyalty increases when they get more familiar with a product class and as they age;

consumers tend to search less when they become more experienced with a product class; and consumers prefer to continue using products they have used before even when technically superior products are available at comparable price. Ratchford (2001) points out that the integration of human capital model and household production model in consumer economics (Becker et al. 1994; Becker and Murphy 1988; Stigler and Becker 1977) provides some unique insights into the role of investments in knowledge in explaining consumer brand loyalty.

Human capital is defined as "knowledge, skill, or expertise embodied in people and acquired through investments in formal or informal education, training, or learning by doing" (Ratchford 2001). According to the household production model, the household or consumer is viewed as a small business combing goods, time, and human capital to produce a positive real-valued vector of outputs, activities, which are analogous to goods or services provided by a business (Ratchford 2001). The goal of all consumers is to maximize the efficiency of this production process, that is, to maximize the output – the utility obtained from the consumption, and minimize the input – the cost incurred to complete the consumption. Whenever a significant amount of human capital is required to consume the product or activity, the efficiency of the consumption process varies across individual consumers due to the different amount of human capital they possess. Consumers accumulate human capital each time they use a brand. Then, the extra human capital associated with that brand makes consumers' future consumption of the same brand more efficient. This view is consistent with what Stigler and Becker (1977) have argued – what appear to be differences in taste are really due to differences in human capital.

Ratchford (2001) provides a useful example to illustrate this point. Making a cake at home requires a lot of time and skills from the baker besides all kinds of materials, such as cake mix and other ingredients, and some equipment, such as an oven. After using the same cake mix repeatedly, the baker is able to memorize the recipe and therefore, is able to make the cake more quickly and with less cognitive effort, and at the same time, get the best quality out of the ingredients. The extra brand-specific skill therefore makes this specific brand of cake mix more attractive relative to the ones with which the baker has no experience. As a result of the brand-specific knowledge, brand loyalty increases.

As pointed out by Ratchford (2001), this framework can be applied to explain consumers' behaviors in other contexts whenever human capital is a major input to the consumption process. Because shopping online is a consumption process that demands significant amount of human capital from consumers, mainly, website knowledge (familiarity about the interface of an online store's website) and product category knowledge, I argue that just as consumers' brand loyalty is driven by consumers' consumption efficiency, consumers' store loyalty online is mainly driven by their shopping efficiency.

2.5 Consumer Learning

The framework proposed by Ratchford (2001) emphasizes the effect of consumer learning on consumers' consumption efficiency. Consumer learning is a process through which consumer knowledge is accumulated through repetitive purchase-related experiences (e.g., Gregan-Paxton and John 1997; Hutchinson and Alba 1991). Consumer

knowledge is defined as the necessary knowledge that enables a consumer to perform product-related tasks successfully (Alba and Hutchinson 1987). A large amount of literature has demonstrated the powerful effects of repetition on consumers' performance of various tasks. In general, it has been found that tasks are performed more rapidly and make smaller demands on cognitive resources after more repetitions. Consumer learning is the key. Repetition gives consumers the chance to accumulate more knowledge, and the accumulated consumer knowledge will reduce the cognitive effort needed to perform some components of the task. The freed cognitive resources then become available for other components of the task, and overall performance improves (e.g., Einhorn and Hogarth 1987; Hoyer 1984; Payne 1976; Russo and Dosher 1983).

The general findings related to consumer learning in the literature can be extended to the context of consumers' online shopping. Shopping online requires two types of consumer knowledge – product category knowledge and website knowledge. While the importance of product category knowledge on consumers' purchase decision making has been widely documented in the literature (e.g., Holyoak 1984; Sternberg 1986; Weisberg and Alba 1981), no previous studies have ever examined how consumers' shopping behaviors are influenced by their store or website knowledge with an exception of Park, Iyer, and Smith (1989). Using a controlled field experiment, they investigated how time pressure and store knowledge jointly influence consumers' purchase decisions such as unplanned buying, brand/product class switching, and purchase volumes. In their study, store knowledge is defined as "the information consumers have about a specific store's layout and floor configurations, including locations of products and brands, based on repetitive shopping experiences in that store" (Park et al. 1989, p.423). They found that

consumer store knowledge affects their information search patterns in the store and the extent to which their brand choices are influenced by the stimuli in the shopping environment. However, they did not explicitly examine how consumer store knowledge influences their decision making efficiency.

Just as consumers need store knowledge to shop at physical stores, website knowledge is necessary for consumers to shop online. In the context of online shopping, what consumers must deal with is a computer interface – the retailers' website. Significant cognitive effort is needed for consumers to learn how to navigate the website in order to complete various purchase-related tasks online, such as searching for relevant product information, placing the selected items in the shopping cart, and entering your billing and shipping information to check out the items. A large body of website usability literature has focused on issues such as the measurement of website usability and the influence of website usability on users' satisfaction with the website (Agarwal and Venkatesh 2002; Palmer 2002). Consistently, previous studies in this stream have emphasized that the importance of website usability relies on the fact that significant cognitive cost is normally incurred by users to function at a website.

Learning plays an important role in helping consumers overcome this major hurdle of online shopping. Lee, Dreze, and Zufryden (2003) point out that repeat visits to a website give consumers the opportunity to learn about various site features or about the quality and the limitations of the information provided by the web site. I argue that through this learning process, consumers' website knowledge can significantly affect their online shopping efficiency. Each time consumers shop at an online store, they become more familiar with the online store's website interface. The accumulated website

knowledge will then reduce the cognitive cost incurred when performing various purchase-related tasks on the website and improve overall shopping efficiency in the future.

2.6 Retailer Learning

As both retailers and consumers participate in the shopping process, the level of service offered by retailers also influences consumers' online shopping efficiency.

2.6.1 Functions of Retailer Services

According to Betancourt and Gautschi (1993), consumers incur various transaction cost during their consumption process, and a major function of retailers is to provide various distribution services to reduce consumers' transaction cost. In the traditional retail context, consumers' transaction cost primarily includes direct time cost, direct transportation cost, adjustment cost, psychic cost, storage cost, and information acquisition cost. With the existence of consumers' transaction cost, the basic function of retailers is to offer a series of distribution services that can potentially reduce consumers' transaction cost, which include ambiance, product assortment, accessibility of location, availability of information, assurance of product delivery in desired form at desired time.

Every retailer provides some level of each of these services. Indeed, it has been suggested that retail businesses are actually service businesses. Competing retailers frequently sell the identical goods and service is the only means of differentiation (Berry and Gresham 1986). In the retail system, the total transaction cost is shared by consumers and retailers. When retailers offer higher level of services, consumers' transaction cost is reduced at the expense of higher operational cost incurred by retailers.

In other words, the transaction cost is shifted from consumers to retailers. In this system, just as consumers are trying to maximize their shopping efficiency, retailers are tying to maximize their operational efficiency – to choose the optimal level of services that will maximize their profits subject to resource constraints.

Although the specific types of transaction cost incurred by consumers and the distribution services offered by retailers may differ in online and offline contexts, the nature of the retail system is still the same, and therefore, the framework proposed by Betancourt and Gautschi (1993) can be directly extended to the online retail setting. Thus, I suggest that the level of services offered by online retailers directly influences consumers' online shopping efficiency.

2.6.2 Retailer Learning and Retailer Services

Each time a consumer shops in a retail store, two types of learning occurs simultaneously – consumer learning and retailer learning. When consumers are acquiring more knowledge about the particular retail store, such as its layout, the retailer is acquiring more knowledge about each individual customer, such as their product preferences. From the birth of commerce, knowledge of one's customer has been a precondition of a successful enterprise. Retailers who have acquired more knowledge about their customers are able to offer a unique, personalized shopping experience and make transactions easier and more pleasant. This is exactly what many Pop-and-Mom stores have done to win their customers' patronage. Although consumer learning has been extensively studied in the marketing literature (e.g., Beattie 1982, 1983; Chi 1983; Hutchinson 1983), the effect of retailer learning on consumer shopping behavior has not received sufficient attention from researchers.

The main reason that retailer learning has long been neglected in the literature is that in traditional markets, large-scale retailer learning is prohibitively expensive. The conventional processes of collecting and analyzing customer data in a retail environment require a huge investment of time and money. As a result, many retailers never analyze all the data available to them and the information is effectively lost. The emergence of the Internet has revolutionized the way retailers are interacting with their customers. Conceptually, the Internet represents an extremely efficient medium for accessing, organizing, and communicating information. As a marketing channel, the Internet has three unique features: (1) the ability to inexpensively store vast amounts of information at different virtual locations; (2) the availability of powerful and inexpensive means of searching, organizing, and disseminating such information; (3) interactivity and the ability to provide information on demand (Peterson and Balasubramanian 1997). These unique features of the Internet have made the collection and analysis of large volume of individual consumer information automatic and effortless (Walsh and Godfrey 2000). Thus, retailer learning has become increasingly efficient.

Based on the amount of retailer learning required, services offered by online retailers can be classified into two categories: personalized services and generalized services. Personalized services seek to treat the customer as an individual with very specific needs and require relatively higher levels of retailer learning. In contrast, generalized services are standardized services provided to all customers and minimum retailer learning is needed. As argued by Betancourt and Gautschi (1993), the level of retailers' services directly influence consumers' transaction cost. Analogously, I argue

that the level of personalized services offered by online retailers will have a direct impact on consumers' online shopping efficiency.

2.7 Conceptual Model

Based on the literature reviewed above, I derive the conceptual model presented in Figure 2. The core ideas of the conceptual framework can be summarized as follows. Two types of learning occur each time consumers shop online – retailer learning and consumer learning. Through the learning process, retailers acquire more knowledge about individual customers so that they are able to provide a higher level of personalized services to their customers. At the same time, consumers acquire more product category knowledge and store/website knowledge so that they are able to complete various purchase-related tasks on the website more quickly and easily. Therefore, consumers' shopping efficiency is jointly determined by the quality of retailers' personalized services building upon retailer learning and consumers' product category knowledge and website knowledge accumulated through consumer learning. Finally, higher consumer shopping efficiency leads to higher consumer store loyalty.

[Insert Figure 2 Here]

2.8 Summary

In this chapter, I reviewed previous literature in the following areas: (1) personalization and recommender systems, (2) customer loyalty, (3) production function and human capital model, (4) consumer learning, and (5) retailer learning. The review of previous studies on personalization and recommender systems reveals that no empirical

work has ever examined the impact of PPRs on consumer store loyalty from a consumer behavior perspective, a gap the current study is going to address. Existing literature in the rest four areas forms the theoretical foundation of the conceptual model developed in this chapter. In the following chapter, I present the research model and discuss the hypotheses.

CHAPTER THREE – HYPOTHESES DEVELOPMENT

Drawing upon the conceptual model developed in Chapter Two, in this chapter, I propose a research model to investigate how PPRs offered by online retailers influence consumers' store loyalty as shown in Figure 3. I argue that higher quality PPRs building upon retailer learning and higher consumer product category knowledge and website knowledge accumulated through consumer learning can effectively increase consumers' online product brokering efficiency, which in turn leads to higher consumer store loyalty. In addition, the impact of PPRs on consumers' online product brokering efficiency is moderated by consumers' product category knowledge.

[Insert Figure 3 Here]

3.1 Consumer Input to Recommender Systems and the Quality of PPRs

The "quality of PPRs" is defined as the extent to which the recommended products match consumers' preferences in a particular purchase occasion. Some literature has studied the various technical factors that may affect the quality of recommendations, such as the size of the database, the algorithms used, etc. (e.g., Adomavicius and Tuzhilin 2002). Findings from these studies provide important guidance to the designers of recommender systems regarding how to further improve the quality of recommendations. However, almost all previous studies in this stream have ignored an important non-technical factor that may significantly influence the quality of PPRs, individual consumers' input. Recommender systems mainly receive two types of input from individual consumers: (1) purchase history; and (2) product ratings.

Recommender systems generate PPRs according to each individual consumer's profile, which is created mainly based on consumers' purchase history and/or product ratings captured by the vendor's database. Previous research on recommender systems (e.g., Ariely et al. 2004) has shown that, to a large extent, the quality of PPRs relies on accurate profiling of individual consumers, which, in turn, depends on the amount of information gathered about individual consumers. The rationale is that consumers' purchases and product ratings, to some extent, reveal their preference about products in certain categories. By examining the pattern of purchases and product ratings, the recommender system is able to estimate each individual consumer's preference or utility function, and based on that estimate, recommend products that better fit each individual consumer's taste. When consumers make more purchases and/or rate more products, they provide more information to the recommender system, which in turn is able to generate a more accurate profile of individual consumers, and ultimately, produce higher quality PPRs.

3.2 Consumer Online Product Brokering Efficiency

Product brokering is an important stage consumers need to go through to complete a purchase. "Consumer online product brokering efficiency" is defined as the ease, accuracy, and speed of making purchase decisions at an online store. When evaluating consumers' online product brokering efficiency, we need to consider both the input (information search and processing cost) and the output (the quality of the decision or choice made by consumers). Higher online product brokering efficiency can be

achieved through either lower online product brokering cost, or higher online product brokering quality, or both.

3.2.1 Quality of PPRs and Online Product Brokering Efficiency

According to the consumer information search and decision making literature, consumers adapt their decision making strategies to specific situations and environments (Payne 1982). When in complex environments, consumers are often unable to evaluate all alternatives available in great depth prior to making a choice (Beach 1993). Instead, they tend to use a two-stage process to reach their decisions, product screening stage and product evaluation stage, where the depth of information processing varies by stage (Payne 1982; Payne, Bettman, and Johnson 1988). First, at product screening stage, the consumer screens a large set of relevant products, without examining any of them in great depth, and identifies a subset that includes the most promising alternatives, which is the so-called consumers' consideration set. Subsequently, at product evaluation stage, the consumer evaluates alternatives in the consideration set in more depth, performs comparisons across products on important attributes, and makes a purchase decision (Haubl and Trifts 2000).

Well-designed recommender systems can effectively improve consumers' information screening efficiency at the first stage. PPRs save consumers' time and cognitive effort in locating and evaluating product information at product screening stage, or reduce consumers' total information search and processing cost, so that consumers who either do not have the ability or just do not have enough motivation to search and process information are now able to form a high-quality consideration set with minimal effort for further evaluation. Just as Alba et al. (1997) have pointed out, the most

important benefit of online shopping to consumers is electronic screening. They assert that without screening, there is little benefit to the consumer of having access to a dramatically increased pool of options on the Internet. "It matters little whether the underlying assortment has 100 or 100,000 alternatives if consumers would stop searching long before the larger inventory would come into play." (Diehl, Kornish, and Lynch 2003). With accumulated knowledge about individual consumers the recommender system is undertaking those resource-intensive but standardizable information search and processing on behalf of consumers, thus freeing up some of the human decision maker's information processing capacity and other limited resources, such as time (Haubl and Trifts 2000). Then, these freed additional resources can be delegated by human decision makers to performing an in-depth product evaluation task at the second stage, and thus, reaching more informed purchase decisions. Moreover, with limited time and cognitive resources, normally, at product screening stage, consumers are not able or not willing to search the whole database exhaustively to locate the items that best match their preference, which may prevent them from forming a high quality consideration set. By searching the whole database on behalf of individual consumers, recommender systems are able to find items that consumers like but cannot find on their own, and present consumers with a higher quality consideration set for further evaluation, which in turn leads to a higher quality purchase decision. In sum, the potential of recommender systems to improve consumers' online product brokering efficiency relies on their ability to form a higher quality consideration set for consumers, and at the same time, free consumers' various resources from the tedious information screening task at product

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screening stage, thereby enabling consumers to devote more resources to their in-depth evaluations at product evaluation stage.

However, the availability of recommender systems does not necessarily improve consumers' online product brokering efficiency. The extent to which PPRs increase consumers' online product brokering efficiency is largely determined by the quality of PPRs, i.e., how closely the recommended products match individual consumers' preferences. When the recommender system has a utility function that is close to that of a consumer's, it can sort through thousands of options and narrow the alternatives to a handful that best match the utility function of the consumer. That is, they present a high-quality consideration set to the consumer. The consumer then expends time and cognitive effort only to inspect and evaluate the recommended few but is able to make a decision or choice of the same quality as if he or she had searched exhaustively through the entire inventory of an online store or mall. A well-designed recommender system is like a super salesperson with excellent knowledge about both the product category and the consumer (Alba et al. 1997). It lowers information search and processing cost by saving the consumer the effort of directly inspecting information on products with low likelihood of being chosen (Diehl et al. 2003). In contrast, if recommender systems fail to accurately estimate individual consumers' utility functions, they will not be able to efficiently screen product information and form a high quality consideration set on behalf of consumers. When PPRs match consumers' preference poorly, they will become useless. Consumers will end up either ignoring the recommendations and having to perform the information search and processing by themselves, or making ill-informed

purchase decisions. In this case, consumers will not experience any improvement in their online product brokering efficiency by receiving PPRs.

In summary, by performing the product screening task on behalf of individual consumers, recommender systems can potentially reduce consumers' total online product brokering cost (the input of the product brokering process) and at the same time, improve consumers' online product brokering quality (the output of the product brokering process). The higher the quality of PPRs, the higher the consumers' online product brokering efficiency. Based on the above discussion, I propose the following hypotheses:

Hypothesis 1a: The quality of PPRs has a negative effect on consumers' online product brokering cost.

Hypothesis 1b: The quality of PPRs has a positive effect on consumers' online product brokering quality.

3.2.2 Consumer Learning and Online Product Brokering Efficiency

Consumer learning is a process whereby consumers accumulate consumption related knowledge or skills from various sources such as their previous consumption experience and advertising (e.g., Gregan-Paxton and John 1997; Hutchinson and Alba 1991). Consumers mainly acquire two types of knowledge from every shopping experience – product category knowledge and website knowledge, both of which can significantly affect their online product brokering efficiency. In general, although the impact of prior product category knowledge on consumers' product brokering has been extensively studied in the literature, how consumers' website knowledge influences their product brokering has not received sufficient attention.

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Accumulated Product Category Knowledge and Online Product Brokering Efficiency

According to the consumer learning literature, typically, consumers' product experience and knowledge acquired through learning has a strong impact on their ability to solve problems (Holyoak 1984; Sternberg 1986; Weisberg and Alba 1981). In situations where a problem is familiar, prior experience may lead to the direct retrieval of a prior solution, as in the case of routinized problem solving (Howard and Sheth 1969). In situations where the problem is new, expertise allows an individual to efficiently generate and evaluate potential solutions (Voss, Vesonder, and Spillch 1980).

In the context of consumer product brokering, the problem is a need and the solution is a need-satisfying product. Compared to novices, expert consumers possess greater factual knowledge, more highly differentiated knowledge, and superior analytic skills (Alba and Hutchinson 1987). The impact of consumers' product category knowledge on their product brokering efficiency is mainly reflected in the following aspects: first, experts use more automated thinking processes than novices (Larkin, McDermott, Simon, and Simon 1980; Shiffrin and Schneider 1977). Automaticity often speeds up a process without a subsequent loss in the quality of performance and, thus, may free up resources that can be delegated to other cognitive tasks (Chi, Glaser, and Rees 1982). Second, experts and novices differ in terms of the amount and structure of information stored in their memory that can be recalled for later product brokering. Whenever decisions are memory-based, knowledge may afford the expert an opportunity to use processing and decision strategies that are very different from the ones the novice

may use (Alba and Hutchinson 1987). Given the chance to learn the same information before making a decision, the expert may be able to rely on memory, whereas the novice may again need to engage in the external search or else make an ill-informed decision.

Third, the quality of consumer product brokering is strongly influenced by both the quantity and quality of information processed by consumers. It has been found that experts have superior ability to notice the relative differences in the importance, relevance, and consistency of facts contained in a message (Brewer and Nakamura 1984; Hastie 1981; Taylor and Crocker 1981). Experts are able to utilize the most important and relevant information from the environment and their memory to make their decisions.

Finally, comprehension differences exist between experts and novices. Experts are able to perceive how different attributes relate to one another, whereas novices perceive, at the extreme, a list of unrelated facts. These comprehension differences may lead to differences in information load. Whereas expertise leads to relatively effortless organizing of the stimuli, consumers who lack expertise may struggle to understand how one attribute is related to another. Moreover, for experts, by chunking related pieces of information, the effective capacity of their working memory can be expanded (Chase and Ericsson 1982).

In sum, consumers with greater product category knowledge enjoy significant advantages during the product brokering process. They expend less time and incur cognitive cost while performing the same amount of information search and processing. At the same time, they are able to make better use of all the available information to reach an informed purchase decision. Therefore, I argue that the amount of consumers' product category knowledge accumulated from previous consumption will make their

future product brokering more efficient. Based on the above discussion, I propose the following hypotheses:

Hypothesis 2a: Consumers' product category knowledge has a negative effect on their online product brokering cost.

Hypothesis 2b: Consumers' product category knowledge has a positive effect on their online product brokering quality.

Accumulated Website Knowledge and Online Product Brokering Efficiency

It has been observed that in traditional retail settings, knowledge about the layout of a retail store helps consumers locate the products they are looking for easily and quickly (Johnson, Bellman, and Lohse 2003; Kahn and McAlister 1997). As consumers, probably all of us have had the following experience: it takes significant amount of time and effort to find the products you are looking for when going to a retail store for the first time or when the layout of a store has changed, but it gets easier and easier with more repeat shopping trips.

The situation is little more complex in the context of online shopping. Electronic technology makes online shopping experience totally different from what happens in the offline context. With online purchasing, the physical store environment no longer exists, and the shopping experience is converted into a human-website interaction (Chen and Dubinsky 2003). Thus, online consumers can be viewed as dual players. They are both customers of a retail business and users of information technology (Cho and Park 2001). Because a huge amount of product information is often provided by online retailers, and the organization and presentation of the information differs greatly across online stores,

finding relevant information and making evaluations on a new website is always a daunting task. Thus, sufficient knowledge about the interface of an online store's website is essential for a consumer to complete various purchase-related tasks in the online environment (Kolesar and Galbraith 2000).

Consumer learning, again, plays an important role in helping consumers overcome these hurdles of online shopping. Each time consumers shop at an online store, they become more familiar with the interface of its website. The accumulated knowledge about a particular online store's website will allow them to perform the information search and processing more easily and quickly at product screening stage by saving them significant amount of time and cognitive effort in navigating the website. The freed time and cognitive resources can then be devoted to more in-depth information processing at the product evaluation stage, and increase consumers' chance of making a better purchase decision. Thus, higher online product brokering efficiency will be achieved.

Using the Media Metrix panel data, Johnson, Bellmand, and Lohse (2003) found that consumers' website visit duration declines the more often a site is visited. This decrease in visit time follows the same power law that describes learning rates in other domains of individual, group, and organizational behavior. They concluded that just as practice improves proficiency with other tasks, visitors to a website appear to learn to be more efficient at using that website the more often they use it. However, as they did not control for other possible factors that may also influence consumers' site visit duration, their study does not provide direct and strong evidence that the decline in site visit duration is due to consumer learning. Therefore, I argue that the relationship between

consumers' website knowledge and their online shopping efficiency still needs to be empirically tested.

Based on the above discussion, I propose the following hypotheses:

Hypothesis 3a: Consumers' website knowledge has a negative impact on their online product brokering cost.

Hypothesis 3b: Consumers' website knowledge has a positive impact on their online product brokering quality.

3.2.3 The Moderating Effect of Consumer Learning

PPRs are just one type of external information sources available on the website when consumers engage in online product brokering. The impact of PPRs on consumers' online product brokering efficiency depends on the extent to which consumers are willing to utilize this information when making their purchase decisions.

Although a large amount of literature has examined the factors that determine the amount of consumer information search (e.g., Beatty and Smith 1987; Moorthy, Ratchford, and Talukdar 1997), our understanding about consumers' choice of various information sources is still very limited. Information sources can be classified into two general categories, internal sources and external sources. Internal sources mainly refer to consumers' memory, and external sources include all other information sources. When making purchase decisions, consumers can either search from their own memory, which is called internal search, or resort to other information sources, termed external search. As pointed out by Ratchford, Lee, and Talukdar (2003), a consumer's process of information search and acquisition can be thought of as a production process in which the consumer seeks to maximize the difference between the utility gain and the cost of

search. Information sources can usefully be identified as input to this production process, in that time and cognitive effort with each source leads to increased information and ultimately, a better decision. This framework implies that when consumers need to gather information to complete a decision making task, they tend to utilize the most efficient information source.

Although PPRs are available to all consumers, the relative efficiency of utilizing this piece of information is different for consumers with different levels of prior product knowledge and website knowledge.

As discussed previously, consumers go through two stages when making decisions in a complex environment – product screening stage and product evaluation stage (Payne 1982; Payne et al. 1988). PPRs can improve consumers' information search and processing efficiency at the screening stage only if they are utilized by consumers.

There are three approaches that consumers can use to gather product information on the website at the screening stage: recalling from their own memory, adopting PPRs, i.e., allowing the recommender system to conduct the screening on their behalf, and performing the information search on their own. Which approach is the most efficient depends on both consumers' product category knowledge and website knowledge, while the likelihood of utilizing personalized recommendations is mainly determined by consumers' product category knowledge. When consumers lack sufficient product category knowledge, they will experience significant difficulty in recalling any useful information from their own memory. If they choose to perform the information search on their own, it will be challenging for them to figure out which product information they should look for. Furthermore, processing the retrieved information also could be a

problem. In this situation, PPRs are always the most efficient approach regardless of consumers' website knowledge. In contrast, when consumers possess high product category knowledge, which approach to use also depends on their website knowledge. When their website knowledge is high, both memory recall or performing the information search on their own are efficient, while when their website knowledge is low, internal search is definitely the best choice. In both situations, PPRs are the least efficient approach.

In sum, PPRs are a more efficient information source for consumers with lower product category knowledge and thus, are more likely to be utilized by these consumers at the product screening stage. As PPRs only influence consumers' online product brokering efficiency when they are utilized by consumers, I argue that the relationship between the quality of PPRs and consumers' online product brokering efficiency will be stronger for consumers with lower product category knowledge.

Based on the discussion above, I propose the following hypotheses:

Hypothesis 4a: The effect of the quality of PPRs on consumers' online product brokering cost is stronger for consumers with lower product category knowledge.

Hypothesis 4b: The effect of the quality of PPRs on consumers' online product brokering quality is stronger for consumers with lower product category knowledge.

3.2.4 Control Variables for Online Product Brokering Efficiency

According to the existing literature, there are other aspects of online retailers' services that may also influence consumers' online product brokering efficiency, and therefore, I include them as controls in the research model.

Website usability. Previous e-commerce research has identified the following features of a well designed website: (1) good organization of information, (2) uncluttered screens, (3) easy-to-navigate, and (4) fast presentations (Eighmey and McCord 1998; Fram and Grady 1995; Manes 1997; Szymanski and Hise 2000). Consumer product brokering online mainly involves information search and processing. Good information organization, easy-to-navigate, and fast presentations will reduce consumers' time and cognitive effort in locating and retrieving the product information they are looking for, and uncluttered screens will reduce consumers' time and cognitive effort required to retrieve and process product information. Therefore, a better-designed website can increase consumers' online product brokering efficiency.

Product selection. A wider selection of products is one of the major attractions of online shopping to many consumers. Compared to their counterparts in traditional markets, online stores enjoy almost unlimited "virtual inventory". It has been observed that Amazon.com carries millions of book tiles, while a large brick-and-mortar bookstore can carry only 150,000 titles (Bianco 1997). Product selection can be further divided into breadth (different product lines) and depth (different varieties within a product line). Superior depth of product selection will reduce consumers' time and cognitive effort to find the exact products they are looking for. It is especially valuable to consumers when the items they are interested in are not widely distributed, or produced in limited quantities. Therefore, a wider selection of products will help consumers find the ideal product more easily and quickly, and thus, increase their online product brokering efficiency.

Quality of detailed product information. Detailed product information refers to the information about any particular product item. For example, at Amazon.com, for products such as DVDs, the following information is available: (1) basic product information such as price, availability, and product image; (2) product details such as the cast, director, rating, release date and format, etc.; (3) non-personalized product recommendations based on item-to-item correlation technology such as "customer who bought this DVD also bought", "explore similar items", "customers interested in this DVD were also interested in these items", "customers who bought this DVD directed by Sofia Coppola also bought DVDs by these directors"; and finally, (4) reviews from different sources such as "our customers' advice", "editorial reviews", "spotlight reviews", and "all customer reviews". In addition, Amazon.com now lets its customers sample some pages from books, and some pieces of music from CDs.

As discussed previously, when faced with tasks of high complexity, consumers usually engage in a two-stage process to make their decisions, product screening stage and product evaluation stage. A well-designed recommender system can perform the information search and processing task on behalf of individual consumers and generate a reasonably small set of alternatives for consumers' further evaluation. At product evaluation stage, consumers then need to examine all the alternatives carefully and make their final choice. High quality detailed product information will reduce consumers' time and cognitive effort in evaluating the products and help them make better choices. Just as the quality of PPRs influences consumers' online product brokering efficiency at product screening stage, the quality of detailed product information directly affects consumers' online product brokering efficiency at product evaluation stage.

3.3 Consumer Shopping Efficiency and Store Loyalty

Although consumer brand loyalty has been extensively studied in the consumer behavior literature, the household production function and human capital framework proposed by Ratchford (2001) provides a new perspective for us to understand this phenomenon. In this framework, it is argued that consumers' brand loyalty is mainly driven by their consumption efficiency. In other words, consumers are loyal to a brand because the human capital (knowledge and experience needed to consume the product) accumulated from previous consumption helps them to consume the same brand more efficiently in the future than any other brands. As observed by Ratchford (2001), this framework can be extended to explain consumers' behavior in other contexts whenever human capital is an important input to the consumption process. Therefore, to judge whether it is appropriate to extend this framework to explain consumers' store loyalty online, we need to evaluate whether online shopping is a consumption activity that requires a significant amount of human capital.

In general, shopping online requires two types of knowledge from consumers – product category knowledge and website knowledge. The importance of product category knowledge and website knowledge on consumer online product brokering efficiency has been discussed earlier in this chapter. Because human capital – consumers' product category knowledge and website knowledge – is an important input to consumers' online shopping process, I argue that the consumption efficiency framework proposed by Ratchford (2001) can be extended here to explain consumers'

store loyalty online, that is, consumers' store loyalty online is mainly driven by their overall shopping efficiency.

As discussed previously, in general, consumers' shopping process is comprised of six stages: (1) need identification, (2) product brokering, (3) merchant brokering, (4) negotiation, (5) purchase and delivery, and (6) post-sales service (Howard and Sheth 1969; Moukas, Guttman, and Maes 1998; Nicosia 1966). Since the focus of this study is on consumers' shopping efficiency at an online store, need identification and merchant brokering are not relevant here, because under most circumstances, they are the two stages consumers must go through before entering an online store. In addition, in most online retail stores, product prices are usually fixed and consumers do not need to negotiate with the vendor, and thus, the negotiation stage is not relevant here. Therefore, in this study, consumers' overall shopping efficiency includes product brokering efficiency, purchase efficiency, delivery efficiency, and post-sales service efficiency, which jointly influence consumers' online store loyalty. Because the focus of this study is on consumers' online product brokering efficiency, consumers' shopping efficiency at all other stages are used as control variables in the model.

Based on the above discussion, I propose the following hypotheses:

Hypothesis 5a: Consumers' online product brokering cost has a negative effect on their store loyalty.

Hypothesis 5b: Consumers' online product brokering quality has a positive effect on their store loyalty.

3.4 Summary

In this chapter, drawing upon the conceptual framework developed in Chapter Two, I presented a research model that explains how PPRs influence consumer store loyalty in the online shopping environment. In the research model, I argue that higher quality PPRs building upon retailer learning and higher level of consumer product category knowledge and website knowledge accumulated through consumer learning increase consumers' online product brokering efficiency, which in turn leads to higher consumer store loyalty. Moreover, the impact of PPRs on consumer online product brokering efficiency is moderated by consumer product category knowledge. In the following chapter, I describe the design of an empirical study to test the research model.

CHAPTER FOUR – METHODOLOGY

In this chapter, I describe the design of an empirical study to test the research model proposed in Chapter Three. The final design of the study was developed based on the results of four rounds of pretests and three rounds of pilot studies. A two-phase lab experiment was used for the data collection to ensure that the core variable – the quality of PPRs – had sufficient variance for statistical analysis. In phase I, subjects' ratings about top DVD sellers were collected and two days later, in phase II, they went to a computer lab and completed a simulated purchase at Amazon.com – to pick two DVD items for themselves subject to a budget constraint and the quality of PPRs they received at Amazon.com was manipulated. A total of 253 undergraduate students in the business school participated in the experiment. All the constructs were measured either using self-developed scales or by adapting existing scales to the context of the current study. The research model was tested using a structural equation modeling approach.

The rest of this chapter proceeds as follows. First, I present the original study design, which includes the target website, target product category, measurement, and design of the experiment. Then, I briefly report all the changes made to the original plan during pretests and pilot studies. Finally, I describe the study design for the final data collection.

4.1 Original Experimental Design

4.1.1 Target Website

In general, online retailers offer two types of product recommendations – personalized recommendations (PPRs) and non-personalized recommendations. By

definition, PPRs are recommendations targeting individual consumers, so that different products are recommended to different consumers based on their preferences, which are estimated by the recommender system with information provided by individual consumers such as their purchase history and product ratings. For example, at Amazon.com, items recommended under "Your Recommendations" are personalized recommendations because these recommendations are generated for individual customers based on their previous purchases and/or product ratings. Offering PPRs requires a website to recognize individual customers.

In contrast, the other type of product recommendations widely offered by online retailers are generated by a technology called item-to-item correlations. For example, many online stores recommend products in the forms of "customers who bought this also bought …", or "similar products", or "related products" when consumers are inspecting a particular product or adding a product to their wish list or shopping cart. Offering such recommendations does not require the site to recognize individual consumers. The items recommended are only determined by the item consumers are inspecting at a particular moment and have nothing to do with individual consumers' previous purchases and product ratings. If two consumers are inspecting the same item, they will get the same product recommendations regardless of their preference or taste. This type of product recommendations is therefore non-personalized.

As a leader in implementing cutting-edge information technologies, Amazon.com has developed one of the most sophisticated recommender systems in the online retail industry. More important, after an investigation of online retailers in several product categories, I found that although many online stores were offering product

recommendations at that time, Amazon.com was one of a few that were offering PPRs, the focus of this study. Finally, among the few online stores that were offering PPRs, Amazon.com provided the easiest way for me to manipulate the quality of PPRs, which is discussed later in this chapter. For all the above reasons, I selected Amazon.com as the target website for the study.

4.1.2 Target Product Category

DVDs are one of the product categories first chosen by Amazon.com when they started offering PPRs. Thus, personalized recommendations for DVDs are very familiar to Amazon.com's consumers. In addition, a small-scale survey among MBA students showed that DVDs are one of the most frequently purchased products at Amazon.com among college students. Therefore, in this study, DVDs were chosen as the target product category.

In the literature, products are commonly classified into three categories, search products, experience products, and credence products (Asch 2001; Brucks, Zeithaml, and Naylor 2000; Darby and Karni 1973; Nelson 1974). Search products are defined as products whose qualities and suitability a consumer can determine by inspection prior to consumption. In contrast, experience products are products whose qualities a consumer cannot determine prior to consumption. Finally, credence products are products that the average consumer can never evaluate the level of quality of a product with confidence even after consumption. This product classification scheme is mainly based on the ease of evaluating the quality of a product by average consumers – inspection only, inspection and consumption, or never.

For the purpose of the current study, I classify consumer products into two general categories – objective products and subjective products. The value of subjective products mainly derives from their content, or intangible features, while the utility of objective products mainly come from their physical attributes. Examples of objective products are cars, computers, cameras, toothpaste, etc., and examples of subjective products include books, newspapers, music CDs, software, movie DVDs, etc. From a consumer decision making perspective, these two types of products differ in the way they are evaluated by consumers. The quality of objective products can be objectively evaluated by examining their physical attributes, while the quality of subjective products can only be subjectively evaluated by individual consumers because the utility provided by subjective products is subject to individual consumers' preference and taste. For example, the quality of a computer can be evaluated objectively along several dimensions such as the size of the memory, speed of the processor, etc. and computers with a larger memory and higher speed are perceived to have a higher quality by all consumers. In contrast, there are no criteria that can be used to objectively evaluate the quality of a movie. Individual consumers with different taste will make different judgment when seeing the same movie. It is true that no product evaluation is pure objective or subjective. In other words, all product evaluation has two components, the objective part and subjective part. Whether a product should be classified as an objective product or subjective product depends on which of the two components dominates.

The target product category, DVDs, belongs to the category of subjective products. The fact that their quality can only be subjectively evaluated by individual

consumers significantly affected the operationalization of many constructs and the experimental design in this study.

4.1.3 Manipulation of the Quality of PPRs

The key manipulation in the experiment is the quality of PPRs that is directly influenced by the level of consumer input given to the recommender system. To a large extent, the quality of PPRs relies on accurate profiling of individual consumers, which in turn is affected by the amount of information gathered about individual consumers (Ariely et al. 2004). I argue that by manipulating the level of consumer input – number of items rated by consumers, I am able to manipulate the quality of PPRs generated by the recommender system, keeping all other features of the recommender system constant.

Because the target website for this study was a real website – Amazon.com, in order to ensure that the subjects' history (previous purchases and product ratings) with Amazon.com did not affect the quality of PPRs they received in the experiment, I created a fake account for each subject before the experiment, and during the experiment, all the subjects were required to log on to this fake account to complete their purchase task. The use of a fake account ensures that the recommender system generated PPRs for each subject from scratch based only on product ratings provided by the subjects.

In the experiment, consumer input to the recommender system – number of rated items – was manipulated with four levels: 0, 5, 15, and 30 product ratings. All the subjects were randomly assigned to one of the four treatment groups, and subjects in group 1, group 2, group 3, and group 4 entered 0, 5, 15, and 30 product ratings respectively into their fake account with Amazon.com.

4.1.4 Sample for the Experiment

Undergraduate students in the business school were recruited for this study. This choice was not made out of convenience, but because undergraduate students were an important group of consumers for DVDs, the target product category in this study. The minimum sample size required to detect most of the hypothesized effects was determined based on the results of a power analysis conducted in the pilot study, which is reported subsequently.

4.1.5 Experimental Procedures

The procedures of the experiment are as follows. First, all the subjects were randomly assigned to one of the four treatment groups and their website knowledge and product category knowledge were evaluated. Then, they logged on to Amazon.com as a new customer with fake email and password. Next, they rated a certain number of DVD items they had watched before. Subjects in group 1, 2, 3, and 4 were required to rate 0, 5, 15, 30 DVD items respectively. Finally, they completed a simulated purchase – select two DVD items for themselves subject to a $50 budget constraint and answered a set of questions to evaluate various aspects of this particular shopping experience and indicated their future repurchase intention. Before they started the purchase, they were asked to assess the quality of PPRs. To provide subjects an incentive to take the simulated purchase seriously, a lottery drawing was conducted after the experiment and the winners got the DVD items they had picked in the experiment for free.

4.2 Measurement

4.2.1 Consumers' Input to Recommender Systems

Most recommender systems take two types of input from individual consumers – purchase history and product ratings. The level of consumers' purchase history refers to the total number of similar items consumers have purchased, and the level of product ratings is defined as the total number of similar items consumers have rated. Here, "similar items" means items in the same product category. In this study, because the subjects are not allowed to check out any items during the experiment, the only input they can give to the recommender system is product ratings. Therefore, the level of input to the recommender system was operationalized with the number of similar items rated by consumers.

4.2.2 Quality of PPRs

Previous studies on recommender systems have investigated both objective products and subjective products. In studies using objective products (e.g., Haubl and Trifts 2000) such as backpacking tents and compact stereo systems, consumers are usually asked to specify their preferred values on a set of physical attributes and the weight they want to place on each of these attributes. Then, the utility function of each consumer is calculated. Finally, each recommended item is evaluated by looking at how much utility it can provide to a consumer based on his/her utility function. The higher the utility, the higher the quality of the recommended item. However, for subjective products such as DVDs, consumers' preferences cannot be expressed with different values on a set of physical attributes, and thus, consumers' utility function cannot be estimated and the utility that an item provides to each consumer cannot be calculated.

How closely a recommended item matches consumers' preferences can only be subjectively judged by individual consumers.

In previous studies that focus on product recommendations for subjective products such as movies, the quality of product recommendations is usually measured by consumers' perceptions about the extent to which the recommended products match their preferences or fit their taste (e.g., Adler, Gibbon, and Matias 2002; Adomavicius and Tuzhilin 2002; Geoffrion and Krishnan 2001; Kumar, Jacob, and Sriskandarajah 2000; Tan, Mookerjee, and Moinzadeh 2003). In these studies, the participants are asked to inspect each recommended item and indicate how much they like the item. Because DVDs, the target product category in this study, are subjective products, the quality of PPRs was measured subjectively with consumers' perceptions about the extent to which the recommended items match their preferences or fit their taste in general.

4.2.3 Consumers' Online Product Brokering Efficiency

Rooted in the economics literature, efficiency can be generally defined as the ratio of input and output associated with a production process. To measure consumers' online product brokering efficiency, we need to evaluate both the cost of online product brokering (level of input) and the quality of online product brokering (level of output).

Both objective and subjective measures have been adopted in previous studies to measure consumers' product brokering cost. Objectively, consumers' product brokering cost has been measured using the total amount of information search and processing performed by consumers, which are operationalized as the total amount of time expended and the total number of alternatives evaluated before consumers reach a purchase decision (Haubl and Trifts 2000).

Alternatively, consumers' product brokering cost can be assessed with consumers' subjective evaluations in terms of the difficulty of making a purchase decision. In the study by Chatterjee and Heath (1996), consumers' product brokering difficulty was measured using a three-item 21 point scale ranging from -10 to +10: not at all difficult/very difficult, not at all simple/very simple, and not all likely to regret/very likely to regret. However, due to different purposes, the product brokering difficulty scale developed in their study does not very clearly distinguish consumers' product brokering cost from consumers' decision making quality. The last item, whether consumers experience regret about their decisions, is more of a measure of consumers' product brokering quality than their product brokering cost. In a study investigating the influence of query-based decision aids on consumer decision making, Pereira (2001) developed a scale to measure consumers' perceived cognitive decision effort, which is defined as the psychological cost of processing information, or the ease with which the subjects can perform the task of obtaining and processing the relevant information in order to arrive at a choice. The validity and reliability were examined with an empirical test, and the reported Cronbach's coefficient alpha was 0.92.

In this study, the scales developed by Chatterjee and Heath (1996) and Pereira (2001) were combined to measure consumers' perceived online product brokering cost. In addition, consumers' total decision making time was also collected as an objective measure of consumers' decision making cost.

Compared to online product brokering cost, consumers' online product brokering quality is more difficult to evaluate. Here, consumer online product brokering quality is defined as the extent to which the purchased item(s) meets their needs or matches their

preferences. Almost all previous research on consumer product brokering has been conducted in the context of objective products such as cameras. The quality of an objective product can be objectively evaluated along multiple physical attributes, and consumers' product brokering quality is usually operationalized as follows: as long as consumers choose a non-dominated product, it is a good-quality or efficient decision (e.g., Haubl and Trifts 2000; Payne 1993). However, the quality of subjective products such as DVDs cannot be judged by their physical features and therefore, cannot be objectively evaluated. Therefore, subjective measures have to be used in this study to evaluate the quality of purchased DVD items.

According to existing literature, one possible way to subjectively measure the quality of consumers' purchase decision is the level of consumers' confidence in their purchase decisions (e.g., Bearden, Hardesty, and Rose 2001; Haubl and Trifts 2000; Spence and Brucks 1997; Tsiros and Mittal 2000). In these studies, consumer decision making confidence are assessed by examining consumers' responses to the following statements: (1) the extent to which they are confident that the product they have chosen best fits their needs, and (2) the extent to which they regret the products they have chosen, and (3) the extent to which they would choose the same product if given another chance. Bearden, Hardesty and Rose's (2001) self-confidence scale, Tsiros and Mittal's decision regret scale (2000), and Pereira's (2001) decision confidence scale have been empirically tested and demonstrate satisfactory internal consistency. In this study, the three scales were integrated to measure consumers' decision making confidence.

4.2.4 Consumers' Store Loyalty

In the consumer loyalty literature, consumers' behavioral intention is widely used as a proxy measure of their actual behavior in cross-sectional studies (e.g., Jones, Mothersbaugh, and Beatty 2000; Mittal, Jr, and Baldasare 1998). Consumer loyalty is a multi-dimensional construct as consumers could signal their loyalty to a store in many different ways. The degree of consumers' loyalty can be examined by looking at both their favorable behavioral intentions and unfavorable behavioral intentions (Zeithaml, Berry, and Parasuraman 1996).

Favorable behavioral intentions. Certain behaviors signal that customers are forging bonds with a company. When customers praise the firm, express preference for the company over others, increase the volume of their purchases, or agreeably pay a price premium, they are indicating behaviorally that they are bonding with the company. By integrating research findings and anecdotal evidence, Zeithaml, Berry, and Parasuraman (1996) complied a list of specific indicators of favorable behavioral intentions, which include saying positive things about the company to others (Boulding, Kalra, Staelin, and Zeithaml 1993), recommending the company or service to others (Parasuraman, Berry, and Zeithaml 1991; Parasuraman, Zeithaml, and Berry 1988; Reichheld and Sasser Jr. 1990), paying a price premium to the company, and remaining loyal to the company (LaBarbera and Mazursky 1983; Newman and Werbel 1973; Rust and Zahorik 1993). Here, remaining loyal may be manifested in multiple ways, such as expressing a preference for a company over others, continuing to purchase from it, or increasing business with it in the future.

Unfavorable behavioral intentions. Customers perceiving service performance to be inferior are likely to exhibit behaviors signaling they are poised to leave the company

or spend less with the company. The most extensively studied unfavorable behavior is complaining, which is viewed by many researchers as a combination of negative responses that stem from dissatisfaction and predict or accompany defection (Richins 1983; Scaglione 1988). In sum, specific indicators of unfavorable behavioral intentions suggested by the previous literature include different types of complaining (e.g., complaining to friends or external agencies) and contemplation of switching to competitors. Another indicator of eventual defection is a decrease in the amount of business a customer does with a company.

Adapting this framework to the current study, consumers' behavior intention was measured by assessing how likely consumers were going to take the following actions: (1) say positive things about the company, (2) recommend the company to someone who seeks advice, (3) encourage friends and relatives to do business with the company, (4) consider the company the first choice to buy similar products in the future, (5) do more business with the company in the next few years, (6) continue to do business with the company even if its prices increase somewhat, (7) pay a higher price than competitors charge for the benefits currently received from the company, (8) do less business with the company in the next few years, and (9) take some business to a competitor that offers better prices.

4.2.5 Consumers' Product Category Knowledge and Website Knowledge

Previous studies have used both subjective and objective measures to assess the knowledge level of consumers. Examples of subjective measures include self-reported amount of knowledge (e.g., Bettman and Park 1980; Johnson and Russo 1981, 1984), familiarity (Park and Lessig 1981), or experience (Punj and Staelin 1983) with a certain

product category. Examples of objective measures include a test of attribute-performance

relationships and brand recall (Brucks 1985; Mitchell and Dacin 1996).

Since these two different measures of knowledge are found to be highly related in

some studies but not in others, following Cowley and Mitchell (2003), in the current

study, both subjective and objective measures were used to evaluate consumers'

knowledge about DVDs. Statements about consumers' subjective assessment of their

product knowledge include: (1) their knowledge about popular movies or TV shows, (2)

their familiarity with famous Hollywood actors and directors, and (3) frequency of

watching movies or TV shows. Consumers' knowledge about DVDs was also evaluated

objectively with the total number of items they have watched out of all the items on

Amazon.com's top seller DVD list.

Likewise, consumers' website knowledge was evaluated both objectively and

subjectively in this study. Objectively, consumers' website knowledge was measured

using their frequency of visits to Amazon.com. Subjectively, the participants were asked

to evaluate: (1) their knowledge about Amazon.com's website; (2) their familiarity with

Amazon.com's website; and (3) how frequently they visit Amazon.com's website.

4.2.6 Control Variables

Product selection. Based on the results of hierarchical cluster analysis,

Wolfinbarger and Gilly (2003) developed a multi-item scale to measure consumers'

perception of an online store's product selection. However, the validity and reliability of

this scale were not reported. In this study, six items from Wolfinbarger and Gilly's

(2003) scale were borrowed to measure perceived product selection. The validity and

reliability of this scale were evaluated through pretests and pilot studies, as discussed subsequently.

Website usability and product information quality. In a recent study on Web customer satisfaction, McKinney, Yoon, and Zahedi (2002) argued that website quality can be evaluated along two dimensions - information quality and system quality. In their study, Web information quality is defined as "customers' perception of the quality of information presented on a Web site", and system quality is defined as "customers' perception of a Web site's performance in information retrieval and delivery" (McKinney et al. 2002, p.299). Systematic analysis indicates six multi-item factors for Web information quality and system quality. The six factors of Web information quality are labeled as: (1) relevance, (2) understandability, (3) reliability, (4) adequacy, (5) scope, and (6) usefulness. The Cronbach's alpha exceeds 0.85 for all factors. The six factors of system quality include: (1) access, (2) usability, (3) entertainment, (4) hyperlinks, (5) navigation, and (6) interactivity. However, the Cronbach' alpha was only 0.51 for access and 0.68 for navigation. Empirical tests in the second phase reveal that reliability, understandability, and usefulness are the three most salient dimensions for Web information quality, and access, usability, and navigation are the top three salient dimensions for system quality.

Because the measurement scales developed by McKinney, Yoon, and Zahedi (2002) for system quality and information quality demonstrate satisfactory validity and reliability, they were used here to measure consumers' perceptions of an online store's website design usability and detailed product information quality.

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Purchase, delivery, and post-sales service efficiency. Purchase refers to the

process of placing selected items into a shopping cart, choosing the shipment method,

providing a shipping address, and finally, entering billing information. Purchase

efficiency was evaluated by how easy and fast it is for consumers to check out the items.

Delivery is the process by which the items ordered by consumers are delivered to their

shipping address, and delivery efficiency was evaluated along the following dimensions:

(1) whether the right products are delivered; (2) whether the products are delivered on

time; and (3) whether the products are in good shape when they arrive. Post-sales service

mainly refers to the process of handling product returns. In this study, post-sales service

efficiency was assessed with how easily and quickly consumers are able to get a refund

or replacement when they return the products to the online retailer.

Consumers' previous experience with Amazon.com. As consumers' previous

experience with Amazon.com may also influence their store loyalty, it needs to be

controlled for in the model. Consumers' previous experience was measured using the

total number of orders they have placed with Amazon.com during the past six months.

4.3 Analysis Strategy

The quality of PPRs perceived by the subjects was compared across the four

groups using ANOVA to see if there is any significant difference. If the manipulation is

successful, on average, the quality of PPRs perceived by subjects in the four treatment

groups should be in the following order from the highest to the lowest: group 4, group 3,

group 2, and group 1. In addition, to check if sufficient variance had been generated for

the focal variable of this study – the quality of PPRs, the distribution of this variable was also examined.

A confirmatory factor analysis (CFA) was conducted using Lisrel to examine the psychometric properties of all the measurement scales used in this study (e.g., Agarwal and Karahanna 2000). As the model includes many latent variables, it was estimated using a structural equation modeling technique. Lisrel and PLS are the two most frequently used software packages to estimate structural equation models. Which one should be used in the final data analysis depends on the sample size and the structure of the data set. In general, PLS has more flexibility and has been widely used by IS researchers to estimate structural equation models because it does not have any strong assumptions about the distributions of all the variables in the model and is also better at handling small sample sizes (Agarwal and Karahanna 2000; Chin 1998; Fornell and Bookstein 1982; Lohmoller 1989).

To give a more accurate estimate of interaction effects by accounting for the measurement errors, as suggested by Chin, Marcolin, and Newsted (1996), the following procedures were used to test for the moderating effect of consumer product category knowledge on the effect of the quality of PPRs on consumers' online product brokering efficiency. First, all the indicators measuring the quality of PPRs and all the indicators measuring product category knowledge were centered. Then, each of the centered indicators measuring the quality of PPRs was multiplied with each of the centered indicators measuring product category knowledge, which resulted in multiple products. Finally, a latent variable was created for the interaction term by using all the products as indicators.

4.4 Final Study Design

To refine the measurement scales and design of the study, four rounds of pretests and three rounds of pilot studies were conducted. Based on the results of pretests and pilot studies, the original study design described above was modified for the final data collection. Major changes made during the pilot studies are summarized in Table 1. Details about all the pretests and pilot studies are reported in Appendix 18.

[Insert Table 1 Here]

4.4.1 Experimental Design

The final data collection followed the same procedures of the third-round pilot study. In Phase I, the subjects were given a top seller DVD list on paper and asked to rate all the items they had watched before. After the subjects' product ratings were collected, those who rated fewer than 15 items were dropped from the sample and the rest of the subjects were randomly assigned to two treatment conditions: high input condition (15 product ratings) and low input condition (5 product ratings). Then, I created a fake account for each subject at Amazon.com and entered their product ratings – the first 5 or 15 ratings depending on which treatment condition the subject is assigned to. Two days later, in Phase II, the subjects went to a computer lab and completed a simulated purchase at Amazon.com. During the experiment, the subjects first assessed their website knowledge and product category knowledge. Then, they logged on to their account at Amazon.com and picked two DVD items for themselves subject to a $50 budget constraint. Finally, they evaluated various aspects of this purchase experience and indicate their repurchase intention. While the subjects were browsing at Amazon.com,

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their clickstream data were automatically captured. Similar to the pilot studies, a lottery drawing was offered to all the participants to ensure that they took the simulated purchase as seriously as they would for a real purchase. There were a total of 20 first-prize winners, who won two DVDs they picked in the experiment for free, and 50 second-prize winners, who won one DVD for free. The experimental procedures for the final data collection are presented in Figure 4.

[Insert Figure 4 Here]

4.4.2 Measurement

Based on the results of the third-round pilot study, two major changes were made in the final data collection. First, four statements were added to the questionnaire to measure consumers' perceived information search cost. They were created by revising the statements that measure consumers' perceived decision making cost. As discussed earlier, higher quality PPRs may mainly reduce consumers' information search cost, not information processing cost, measuring consumers' perceived information search cost would help us better understand the impact of PPRs on consumer online product brokering efficiency.

In addition, the scale that measures consumer decision making confidence was modified in two ways because of its poor performance in the pilot studies. First, rather than asking the subjects to evaluate the extent to which they have made the right choice for themselves, in the final data collection, the subjects were asked to assess the extent to which they had made the best choice if they had the chance to search the whole database. What recommender systems can do for consumers is to go through all the items available on a website on behalf of individual consumers and only present to them those items they

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are most interested in. In real life, with limited cognitive and time resources, this is impossible for most consumers to do on their own. Therefore, with the help of high quality PPRs, consumers are able to locate items that best fit their taste among all the items available on a website, rather than just getting items that fit their taste. The modified statements should capture the benefit of PPRs more accurately.

Moreover, the results of pilot studies show that consumer decision making confidence always had a very skewed distribution and failed to generate any interesting results. Given a seven-point Likert scale with "1" indicating "strongly disagree" and "7" "strongly agree", the responses of most subjects centered on a high value. The results are reasonable in the sense that most consumers will feel from somewhat confident to very confident when they are asked these questions immediately after they have made the purchase decision.   This is especially true when the products involved are not very complex and consumers will have no difficulty in evaluating the quality of the products they have picked by themselves. The way these questions were asked could not accurately reflect the subtle difference among consumers in their decision making confidence. To fix this problem, in the final data collection, the statements measuring consumer decision making confidence were kept the same and they were still evaluated by the subjects on a seven-point Likert scale. The only difference was "1" now indicating "somewhat agree" instead of "strongly disagree". This may help improve the distribution of this variable to generate sufficient variance.

The operationalization of all the constructs in the final data collection is summarized in Table 2 and all the measurement items are listed in Table 3. The questionnaire and experimental protocol are presented in Appendix 20.

[Insert Table 2 and Table 3 Here]

4.5 Summary

 In this chapter, I first presented an initial study design to empirically test the research model developed in Chapter Three. Then, I reported the results of pretests and three rounds of pilot studies which were conducted to refine the study design. Finally, I described the study design for the final data collection. In the following chapter, I report and discuss the results of the final study.

CHAPTER FIVE – RESULTS AND DISCUSSION

In this chapter, first, I report the results of final data analyses. A total of 253 undergraduate students participated in this study. Confirmatory factor analysis was conducted using Lisrel to evaluate the psychometric properties of all the measurement scales. The structural equation model was estimated with PLS. The results indicate higher quality PPRs improve consumer online product brokering quality at the expense of higher online product brokering cost. Consumer future repurchase intention is significantly enhanced by higher online product brokering quality and not affected by online product brokering cost. Then, I discuss the implications of the findings, as well as the limitations and contributions of the study. Finally, I suggest directions for future research.

5.1 Sample Description

The final data collection was conducted in April, 2005. A total of 366 undergraduate students in the business school were recruited at Phase I and completed the movie rating part of the study, but only 273 showed up in the lab at Phase II and finished the whole study. Among them, 16 students who rated fewer than 15 items were dropped from the sample. After all the data collection was over, the subjects' clickstream data were examined and four students who did not log on to their own fake account as instructed were eliminated, which resulted in a final sample size of 253. The sample was comprised of 43% females and 57% males with an average age of 21. They had between three and ten years of experience with the Internet and the average was seven years. Out

of the 134 top seller DVDs, the total number of items they had watched ranges from 15 to

134 with the average of 37.   About 61% of them had shopped at Amazon.com at lease

once. The descriptive statistics of the sample are presented in Table 4.

[Insert Table 4 Here]

5.2 Measurement Scale Evaluation

First, a factor analysis was performed using SPSS and the total number of factors

to be extracted was specified in advance. The results showed a very clear pattern (see

Table 5) and the total variance explained by the 16 factors was 89%.

[Insert Table 5 Here]

Next, a confirmatory factor analysis (CFA) was performed with Lisrel. After

several runs of adjustments, the final model showed an adequate goodness of fit (see

Table 7): Good of Fit Index (GFI) = .85, Adjusted Goodness of Fit Index (AGFI) = .82,

Normed Fit Index (NFI) = .91, Root Mean Square Residual (RMR) = 0.04. The normally

recommended threshold for all these indices are: GFI > .90, AGFI > .80, NFI > .90, RMR

< .05 (Joreskog and Sorbom 1993). Although GFI is lower than .90, it is reasonably high

and is considered adequate in many studies (e.g., Purvis, Sambamurthy, and Zmud 2001).

All the paths were significant at α = 0.05 (see Table 6). The following items were

dropped during the CFA process to improve the goodness of fit of the measurement

model: WBKN1 and WBKN2 measuring consumer website knowledge, PRDKN1

measuring consumer product category knowledge, PPR4, PPR5, and PPR6 measuring the

quality of PPRs, DMST4 measuring decision making satisfaction, DMCNF4, DMCNF5,

and DMCNF6 measuring decision making confidence, DEGN4 measuring website usability, and PURCH4 measuring purchase efficiency.

[Insert Table 6 and Table 7 Here]

To further evaluate the discriminant validity of all the constructs, the inter-construct correlation matrix was created. The values on the diagonal are the square root of the average variance extracted (AVE) of each construct. It can be seen from Table 8 that AVE of all the constructs is larger than its correlations with all other constructs, which means that the average variance shared between the construct and its indicators is larger than the variance shared between the construct and other constructs (Agarwal and Karahanna 2000). Therefore, the results indicate that all the constructs in the model demonstrate satisfactory discriminant validity.

Finally, Cronbach coefficient alpha was calculated for each multi-item construct using SPSS and all of them demonstrate very high internal consistency with the alpha greater than .80 (see Table 9).

[Insert Table 8 and Table 9 Here]

5.3 Manipulation Check

As a manipulation check, ANOVA was performed to compare the perceived quality of PPRs between the two groups – high input (15 product ratings) with 126 subjects and low input (5 product ratings) with 127 subjects. The results are consistent with my prediction. Subjects in the high input group perceive the quality of PPRs significantly higher than subjects in the low input group. The results of ANOVA are

presented in Table 10. In addition, the distribution of the quality of PPRs was close to normal, which indicates sufficient variance had been generated for this variable.

[Insert Table 10 Here]

5.4 Hypotheses Testing

Due to the small sample size, Lisrel was not appropriate here for the model estimation. After all the structural paths were added to the measurement model, the total number of parameters to be estimated exceeded the sample size. In this case, Lisrel cannot produce reliable estimates. Therefore, PLS was used instead. PLS has been widely used in the IS literature to estimate structural equation models especially when the sample size is not large enough for Lisrel and the variables do not follow a multivariate-normal distribution (e.g., Agarwal and Karahanna 2000).

To test for the interaction effect of consumer product category knowledge and the quality of PPRs, an interaction term was created by taking the following steps (Chin et al. 1996): First, the three indicators measuring the quality of PPRs and the two indicators measuring product category knowledge were centered. Then, each of the three centered indicators measuring the quality of PPRs was multiplied with each of the two centered indicators measuring product category knowledge, and resulted in six products. Finally, a latent variable was created for the interaction term by using the six products as indicators.

In a PLS structural model, the outer loading of each indicator on its corresponding construct can be interpreted as loadings in a principal components factor analysis

(Agarwal and Karahanna 2000). Table 11 shows that the outer loadings of all the indicators are above .7 and are significant at .001.

[Insert Table 11 Here]

The overview of the model estimation results are presented in Figure 5 and the results for the core model are show in Figure 6 with more details. Due to the complexity of the model, only significant paths are displayed. The path coefficients and explained variance for the model are reported in Table 12 and the results are summarized in Table 13.

[Insert Figure 5, Figure 6, Table 12, and Table 13 Here]

The R-square for total decision making time, ease of decision making, ease of information search, decision making confidence, decision making satisfaction, and repurchase intention were 31.2%, 31.5%, 36.5%, 29.8%, 41%, and 52.7% respectively.

The three core variables in the model – quality of PPRs, consumer product category knowledge, and website knowledge showed significant impact on consumer online product brokering efficiency.

It was found that higher quality PPRs had a significant positive association with consumers' total decision making time, perceived decision making difficulty, ease of information search, decision making confidence, and decision making satisfaction. Consumers' total decision making time can be interpreted as a measure of consumers' total product brokering cost, which has two components – (1) consumer decision making cost, i.e., the cost incurred by consumers to process product information and make their

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judgment, and (2) consumer information search cost, i.e., the cost incurred by consumers to locate the product information they are looking for. Therefore, the results show that although higher quality PPRs reduce consumer information search cost, they increase consumer decision making cost and consumer total product brokering cost. Hypothesis 1a, which posited that higher quality PPRs have a negative effect on consumer online product brokering cost, was not supported and a significant impact was found in the opposite direction.

Consumer online product brokering quality was evaluated from two perspectives: (1) the utilitarian value obtained by consumers from the product brokering process – the quality of the purchase decision they have made, which was measured with consumer decision making confidence; and (2) the hedonic value obtained by consumers – the fun consumers have experienced during the product brokering process, which was measured with consumer decision making satisfaction. It was found that higher quality PPRs had a significant positive correlation with both consumer decision making confidence and decision making satisfaction. Therefore, hypothesis H1b, which posited that higher quality PPRs have a positive effect on consumer product brokering quality, was supported.

Consumer learning – the accumulated website knowledge and product category knowledge – also was also found to have significant influence on consumer product brokering efficiency. First, higher website knowledge was positively associated with ease of information search, but had no significant relationship with consumer decision making time and ease of decision making. Hypothesis 3a, which posited that higher website knowledge has a negative effect on consumer online product brokering cost, was

partially supported. Moreover, higher website knowledge had a significant positive correlation with consumer decision making satisfaction but was not significantly related to consumer decision making confidence. Hypothesis 3b, which posited that higher website knowledge has a positive effect on consumer online product brokering quality, was partially supported.

In addition, it was found that higher product category knowledge was positively associated with consumer decision making time and information search difficulty, but had no significant relationship with ease of decision making, decision making confidence, and decision making satisfaction. Hypothesis 2a, which posited that higher product category knowledge has a negative effect on consumer online product brokering cost, was not supported and a significant effect was found in the opposite direction. Hypothesis 2b, which posited that higher product category knowledge has a positive effect on consumer online product brokering quality, was not supported.

The interaction effect between the quality of PPRs and consumer product category knowledge was not significant, and therefore, hypothesis 4a, which posited that the relationship between the quality of PPRs and consumer online product brokering cost is stronger for low product knowledge consumers, and hypothesis 4b, which posited that the relationship between the quality of PPRs and consumer online product brokering quality is stronger for low product knowledge consumers, were not supported.

Some control variables were also found to significantly affect consumer online product brokering efficiency: (1) a more usable website was negatively associated with decision making time and positively correlated with ease of decision making, ease of information search, decision making confidence, and decision making satisfaction; (2) a

wider product selection had a negative relationship with decision making time and a negative relationship with ease of decision making; (3) higher quality detailed product information was positively related to decision making satisfaction; (4) higher decision making involvement had a positive association with decision making difficulty and decision making confidence; (5) older consumers spent less time on decision making; and (6) more Internet experience was negatively correlated with decision making time.

Finally, it was found that the two measures of consumer product brokering quality –decision making confidence and decision making satisfaction – had a significant positive association with consumer repurchase intention, however, the three measures of consumer online product brokering cost – total decision making time, ease of decision making, and ease of information search – did not show any significant impact on consumer repurchase intention. Therefore, hypothesis 5a, which posited that higher online product brokering cost reduces consumer repurchase intention, was not supported, while hypothesis 5b, which posited that higher online product brokering quality increases consumer repurchase intention, was supported. Some control variables were also significant in the model: (1) higher expected delivery efficiency was positively associated with consumer repurchase intention; (2) more reasonable prices was positively correlated with consumer repurchase intention; and (3) consumers who had shopped at Amazon.com before had higher a repurchase intention.

The results of hypotheses testing are summarized in Table 14. A series of OLS regression analyses were also conducted (see Appendix 19) and the results were consistent with the PLS results.

[Insert Table 14 Here]

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5.5 Discussion

Before discussing the results, it should be noted that because cross-sectional data was used in this study, all the causal relationships discussed subsequently are not inferred from statistical analyses but from theoretical arguments.

Although it is widely believed that PPRs benefit consumers mainly by reducing their product brokering cost, an interesting and surprising result of this study is that higher quality PPRs may actually increase consumers' product brokering cost.

Consumers mainly incur two types of cost at product brokering stage, information search cost and information processing cost. By searching the whole database on behalf of consumers and making items they are interested in immediately available to them, higher quality PPRs reduce consumers' time and effort in locating those items, thus, higher quality PPRs reduce consumer information search cost. At the same time, higher quality PPRs can increase consumer information processing cost by increasing the size of consumers' consideration set. In this study, the size of consumers' consideration set was not measured explicitly, but empirical evidence from previous studies can provide some support for this conjecture.

Two previous studies have investigated the impact of interactive decision aids such as recommender systems on the size of consumers' consideration set but their findings are contradictory. While Haubl and Trifts (2000) found the availability of an interactive decision aid reduces the size of consumers' consideration set, Pereira (2001) found the opposite.

The products selected in their studies, backpacking tents and compact stereo systems in Haubl and Trifts (2000) and cars in Pereira (2001), have similar characteristics, that is, the quality of these products can be evaluated objectively by examining the value of a set of attributes. The same type of decision aid – Personal Logic – was used in these two studies. Personal Logic is an interactive decision aid and has been implemented in some well-known online stores' website such as Macys. It works in the following way: it first elicits individual consumes' preferences by asking consumers to specify their preferred value for each attribute and the weight for each attribute, then, it calculates the utility each product provides to individual consumers, and finally, it recommends products to consumers in the order of their utility. More over, a lab experiment was used in both the two studies and the experimental design was also very similar. It is therefore surprising that the two studies produced contradictory results.

Haubl and Trifts (2000) argue that because the decision aid can calculate the utility of each product for individual consumers and display the products to consumers in this order, consumers do not need to examine all the products available on a website and can only focus on a smaller set of items that have the highest utility. In contrast, Pereira (2001) argues that because the decision aid performs all the product screening on behalf of consumers, it saves consumers' information search and processing cost at the product screening stage, and the freed time and cognitive resources allow consumers to examine more items and form a larger consideration set.

A major difference between the two studies is the way consumers' consideration set was measured and this may help resolve the inconsistent results. A subjective measure was used by Haubl and Trifts (2000). In their study, the subjects were asked to

recall the number of items they had seriously considered after finishing the purchase task, while Pereira (2001) allowed the subjects to check all the items they want to further evaluate during the product screening process and the number of checked items was used as a measure of consumers' consideration set. Objective measures are always believed to be more accurate than subjective measures and therefore, the findings of Pereira's (2001) study are more plausible.

Therefore, in the context of the current study, when the quality of PPRs improves, consumers are able and willing to form a larger consideration set and inspect more items before they reach a purchase decision. Given a fixed information processing speed and all else being equal, evaluating more items will result in higher information processing cost. This is why, in the current study, a positive relationship was found between the quality of PPRs and consumer decision making time and perceived decision making difficulty.

Because higher quality PPRs influence consumers' information search cost and information processing cost simultaneously but in opposite directions, the impact of higher quality PPRs on consumer total product brokering cost depends on which of the two effects dominates. If consumer total decision making time can be interpreted as a measure of consumers' total product brokering cost, the finding that higher quality PPRs increase consumer total decision making time implies that the increase in information processing cost outweighs the reduction in information search cost when the quality of PPRs improves in the specific purchase setting of this study.

This finding may sound counter-intuitive. If higher quality PPRs increase consumers' product brokering cost, what is the value of PPRs to consumers? When

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evaluating consumers' product brokering efficiency, we need to consider both the level of input – product brokering cost and the level of output – product brokering quality. It was found in this study that higher quality PPRs increase consumers' decision making confidence and decision making satisfaction.   Recall decision making confidence reflects the quality of the purchase decision made by consumers or the utilitarian value obtained by consumers from the online product brokering process. Higher quality PPRs improve consumers' decision making quality in two ways. First, higher quality PPRs reduce consumers' information search cost so that consumers can devote more time and cognitive resources to information processing and make better judgments. In addition, because PPRs are generated by the recommender system by searching the whole database of a website, which is impossible or very expensive for consumers to do on their own in normal conditions, the recommender system forms a higher-quality consideration set for consumers, which in turn improves the quality of consumers' purchase decision. At the same time, higher quality PPRs increase consumers' decision making satisfaction or the hedonic value obtained by consumers from the online product brokering process. By presenting more interesting items to consumers, higher quality PPRs increase the enjoyment of the decision making process and bring more fun to consumers' online shopping experience.

In sum, the findings of this study indicate that when the quality of PPRs improves, consumers obtain more utilitarian value in the form of higher quality purchase decisions as well as more hedonic value in the form of more fun experienced during the decision making process.

An interesting question that arises based on these findings is: because higher quality PPRs increase consumers' product brokering cost as well as product brokering quality, what is the net effect of higher quality PPRs on consumer's product brokering efficiency? It was found in this study that higher decision making confidence and decision making satisfaction increase consumers' repurchase intention, while the three measures of consumers' decision making cost – decision making time, ease of decision making, and information search cost – do not show significant impact. This finding suggests that when product brokering cost and product brokering quality are considered simultaneously by consumers, product brokering quality gets more weight or is perceived to be more important. This may also imply that the increase in product brokering quality dominates the increase in product brokering cost so that the increase in product brokering cost can be ignored compared to the increase in product brokering quality. In other words, consumers' product brokering quality increases faster than product brokering cost when the quality of PPRs improves so that consumers' product brokering efficiency increases.

In addition, it was found in this study that consumer product knowledge increases consumer total decision making time and information search cost. Although contradictory to my prediction, this finding is consistent with the more recent literature about consumer information search (Alba and Hutchinson 1987; Punj and Staelin 1983). Compared to low knowledge consumers, high product knowledge consumers incur lower unit information search cost, i.e., information search cost per item, but their total information search cost may be higher because they perform a larger amount of information search. However, the amount of information search does not increase

linearly with consumer product knowledge. Moorthy, Ratchford, and Talukdar (1997) argue that the relationship between consumer product category knowledge and the amount of information search should be like an inverted U-shape. The amount of information search conducted by consumers is strongly influenced by consumers' prior perceptions about the product market and not just consumers' unit information search cost. For consumers with low product knowledge, all the products in the market are perceived to be homogeneous and thus there is no need to search. In contrast, for consumers with high product knowledge, all the products in the market are fully differentiated and therefore, there is no need to search either. Although high knowledge consumers incur lower unit information search cost due to their superior ability to analyze, interpret, infer, remember, and cognitively process product information (Moorthy, et al. 1997), they may not perform more information search simply because they do not have the need to search. Finally, consumers with middle level product knowledge see the products in the market partially differentiated and therefore conduct the most amount of information search among the three groups. To test for this possible non-linear relationship between product knowledge and the amount of consumer information search, a quadratic term of product knowledge was added to the model. However, it was not significant. Therefore, findings of this study only support the increasing part of the U-shape curve but the declining part is not revealed here.

Another issue to be noted is that no interaction term was found to be significant in this study. It is hypothesized that PPRs are a relatively more efficient information source for low knowledge consumers and are more likely to be utilized by low knowledge consumers, and thus, the quality of PPRs has a greater impact on low knowledge

consumers. However, this finding implies that there is no significant difference in terms of utilization of PPRs between high knowledge and low knowledge consumers. This is because, in the current study, the quality of PPRs was measured subjectively with consumers' perception about how closely the recommended items match their preferences or fit their taste. When PPRs are perceived to be relevant and useful, they will be utilized by consumers regardless of their product category knowledge. The moderating effect may exist if an objective measure of the quality of PPRs is used in the study.

5.6 Limitations

Prior to discussing the implications of the findings, some limitations of this study should be acknowledged. First, this framework cannot be applied to explain the impact of PPRs on consumers' store loyalty in all situations. A major assumption of this model is that consumers have some product brokering to do when they enter an online store and thus their product brokering efficiency is directly affected by various features of an online store. This assumption may not hold in all circumstances. Sometimes, consumers may have completed all product brokering before they go to a particular online store. When they enter the store, they already know which specific items they want to purchase and will not want to engage in any more product brokering. In these cases, consumers' product brokering efficiency has nothing to do with the services offered by the online store and therefore, will not have any direct effect on their store loyalty.

Second, this study assumes that PPRs are relevant to consumers' purchase decisions. In the experiment, the subjects receive PPRs about DVDs, although the

quality of PPRs differs across treatment groups. In real life, however, consumers may receive totally irrelevant recommendations. For example, books are recommended when consumers are looking for DVDs. Under these circumstances, recommendations will not have any positive impact on consumers' decision making efficiency. The availability of completely irrelevant recommendations may even elicit negative feelings from consumers and lead to lower decision making efficiency. How PPRs influence consumer decision making and store loyalty when recommendations are completely irrelevant is beyond the scope of this study and is an interesting topic for future research.

Third, this study focuses on a single product category – DVDs. The findings may not be generalizable to other product categories. The impact of PPRs on consumer product brokering efficiency may differ across product categories. The potential of PPRs to improve customer retention may vary depending on the characteristics of the products. For example, for products that are not frequently purchased by consumers, the quality of PPRs cannot be high enough to benefit consumers. Moreover, PPRs may be more useful for products such as books, DVDs, or CDs that are related to consumers' taste, which is difficult for consumers to express accurately but can be revealed from their purchases and product ratings. How product characteristics influence the impact of PPRs on consumer store loyalty will be an interesting area to investigate in the future.

Fourth, a student sample was used in this study because they are the major group of consumers of DVDs. However, college students may not represent general consumers. Therefore, the findings of this study can be generalized to consumers with similar characteristics and caution should be taken when generalizing the results to other consumer groups.

Fifth, the data was collected from a simulated purchase in a lab setting. Although lottery drawing was offered to all the subjects to improve their decision making involvement, consumers may behave differently for a real purchase in a natural setting. Other data collection methods should be explored in future research to reach a deeper understanding about this phenomenon.

Sixth, although in the experiment, the subjects were randomly assigned to the two treatment conditions and the quality of PPRs they received was manipulated, consumers' perceived quality of PPRs was used to estimate the model, so this is not a pure experiment. The purpose of the manipulation is just to generate sufficient variance for the core variable – the perceived quality of PPRs. In addition, because all the variables in the model including consumers' perceived quality of PPRs were measured in one time slot, the data is cross-sectional. A significant path in the model can only prove there is a significant relationship between two variables but cannot determine the direction of the relationship. Pure experiments or longitudinal study should be conducted in future research to test all the causal relationships hypothesized in the model.

Finally, a single website – Amazon.com – was used in this study in order to control all the features of recommender systems while generating sufficient variance for the core variable – the quality of PPRs. The results may not be generalizable to other websites. Future research should test this model with data collected from multiple websites.

5.7 Implications

As one of the first empirical studies that investigate whether and how PPRs improve customer store loyalty online, findings of this study have important implications for both researchers and practitioners.

5.7.1 Theoretical Implications

First, findings of this study provide strong empirical support that household production function model can be used as a new theoretical angle to explain customer store loyalty online. Compared to the service quality – customer satisfaction – customer store loyalty framework, the service quality – customer value – customer store loyalty framework more accurately captures the driver of customer store loyalty and can be applied to many different contexts to explain consumers' consumption preferences. Efficiency is an important value pursued by consumers when engaging in various consumption activities. Because consumers incur significant cognitive cost when shopping online, cognitive efficiency has become one of the major drivers of customer store loyalty.

Second, findings of this study show that learning – consumer learning and retailer learning – is playing a key role in improving consumers' online shopping efficiency and store loyalty because online shopping requires a significant amount of cognitive effort. Although focusing on PPRs, the conceptual framework developed in this study can be generalized to understand the impact of personalization on customer store loyalty in general.

Consumer learning as a process to accumulate product category knowledge has been studied extensively in the literature (Holyoak 1984; Sternberg 1986; Weisberg and Alba 1981), however, consumer learning as a process to accumulate store knowledge has received very limited attention (Johnson, et al. 2003; Kahn and McAlister 1997). Accumulating store knowledge is especially important in the online shopping environment when consumers need to interact with an online store's website to complete a transaction. This study provides the first empirical evidence that consumer learning can lead to cognitive lock-in, that is, consumers cannot switch to another vendor without incurring higher cognitive cost.

Compared to consumer learning, retailer learning has long been ignored in the literature. Advances in information technologies have significantly increased the efficiency of retailer learning, which in turn makes large scale personalization a reality. By personalizing their online shopping experience, effective retailer learning can provide more value to customers and therefore improve customer store loyalty. When consumers switch to another store, their online shopping efficiency will suffer. They will not be able to receive the same value without incurring a significant amount of cognitive effort to teach the online store about their preferences and taste. The longer they have stayed with the current store, the more difficult for them to switch.

Third, findings of this study suggest that effective retailer learning requires cooperation from consumers and it is not just a technical issue that can be solely solved by designers of recommender systems. Lack of sufficient data has always been a big challenge for recommender systems to generate high quality PPRs (e.g., Gonul and Srinivasan 1993). Although more rigorous algorithms may help to some extent (e.g.,

Allenby and Lenk 1994; Ansari et al. 2000; Russell and Kamakura 1994), it should be tackled from other perspectives as well. Many factors may affect consumers' motivation to provide product ratings such as the interface of the recommender systems, individual consumer characteristics, and situational factors. Theoretical frameworks and empirical studies are definitely needed to explore this issue.

Fourth, findings of this study imply that the main benefit of PPRs to online shoppers is not the reduced online product brokering cost, as many people have believed, but the improved online product brokering quality – increased utilitarian value and hedonic value obtained from the online product brokering process. This finding suggests that when consumers evaluate their shopping efficiency, they not only consider the cost but also the quality. Consumers are willing to sacrifice their time and cognitive effort to receive more value from the online shopping process. However, when consumers' online product brokering cost reaches a certain level, it may outweigh the benefit received by consumers and PPRs may start to have a negative impact on consumers' store loyalty. More research is needed to investigate if there exists an optimal level of personalization and the impact of over-personalization on consumer shopping efficiency.

Finally, previous studies have concluded that online shoppers are goal-oriented in general (Wolfinbarger and Gilly 2001) and utilitarian value is perceived to be more important than hedonic value. However, findings of this study suggest this is not true. Hedonic value is equally important, if not more important, to online shoppers. A body of IS literature on flow and cognitive absorption (e.g., Csikszentmihalyi 1990; Trevino and Webster 1992; Webster and Ho 1997; Agarwal and Karahanna 2000) may provide some insights to explain this phenomenon. Users can experience a state of flow or have a high

cognitive absorption when interacting with technologies. They are so engaged in the activity and have so much fun that they forget everything else happening in the environment. It has been found that the playfulness and fun experienced by users can significantly increase their usage of technologies (e.g., Agarwal and Karahanna 2000). This may explain why many online firms are trying to make their websites stickier by creating a more enjoyable virtual environment. Theoretical framework and empirical studies are needed to better understand how personalization brings more hedonic value to online shoppers.

5.7.2 Managerial Implications

Findings of this study also have important implications for online retailers. Results of this study show that PPRs have the potential to improve customer retention through the following mechanism: the more purchases made by consumers, the higher the level of input to the recommender system, the higher the quality of PPRs received by consumers, the higher consumers' product brokering efficiency, and finally, the higher the consumers' repurchase intentions. Then, the loop starts again. Unlike other services offered by an online firm, theoretically, PPRs can bring sustained competitive advantage to online firms because it is a strategy that will become more and more difficult for competitors to imitate over time. It takes time and cognitive effort for customers to teach an online store about their preferences and taste in exchange for a more efficient shopping experience. When they switch to another store, their shopping efficiency will suffer or to achieve the same level of shopping efficiency, they have to expend a significant amount of effort to teach this store from scratch. Moreover, a large database is required for a recommender system to generate high quality PPRs and this takes time

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for an online firm to build up. Therefore, personalization in general and PPRs in particular can bring the first movers sustained competitive advantage.

However, a recent report released by Jupiter Research (2003) shows that PPRs are not appreciated by many online shoppers and their impact on consumer store loyalty is very limited. Only 14% of the surveyed consumers say they are more likely to go back to an online store because of personalized services including PPRs, compared to more than 40% say they are more likely to return to stores that has a more user-friendly website.

According to the survey, poor quality is the main reason that PPRs are perceived to be of low value by many online shoppers. Although the quality of PPRs depends on many factors such as the algorithms used by the recommender system and the size of the database, lack of sufficient input from individual consumers has made it very difficult for recommender systems to generate recommendations that closely match individual consumers' preferences. This is especially the case for new customers or customers who do not purchase frequently from an online store.

Previous purchases and product ratings are the two main types of input to recommender systems. Purchase history can be collected automatically and does not demand any explicit effort from consumers, but it takes time to accumulate and also the data itself has more noise. For example, purchase itself does not necessarily mean consumers like this product. Consumers may make the purchase for somebody else or by mistake. In addition, a purchase does not tell the recommender systems how much consumers like this product. The data is in the form of a binary variable representing a preference. As an input to recommender systems, product ratings have a higher quality with less noise. Product ratings reveal consumers' product preferences in more detail,

e.g. on a five-point Likert scale from "I hate it" to "I love it" at Amazon.com. However, product ratings cannot be collected automatically and have to be entered by consumers, and thus, demands a significant amount of time and cognitive effort from consumers. Providing product ratings is like an investment made by consumers today in the form of time and cognitive effort to make their online shopping more efficient in the future. However, the existence of a vicious circle may prevent PPRs from generating any value to both consumers and online firms. Without sufficient input from individual consumers, PPRs generated by the recommender system will have poor quality, and thus, will be perceived to be useless by consumers, which will reduce consumers' motivation to provide product ratings even further.

To persuade consumers to make the initial investment and realize the potential of PPRs, some incentives are necessary at the very beginning in order to start the virtuous circle. For instance, consumers can get some discount when purchasing DVDs if they rate certain number of items. Or, send emails to consumers after the purchase to give them a link to rate the items and offer them a discount for future purchases. And, remind them that they have not rated certain items the next time they visit the website. In addition, the interface of the recommender systems should be improved to reduce the cost incurred by consumers when submitting product ratings. For example, at Amazon.com, consumers can rate only one item at a time. After checking the corresponding box, they have to wait for the window to refresh, then, close the window, and click the next item to rate. In contrast, at NetFlix.com, customers can rate multiple items at the same time. It is much easier and faster. With increasingly intense competition in the online moving renting industry, PPRs have given NetFlix.com an edge over its competitors.

Another important finding is that consumer can be locked in by an online store through consumer learning. Results show that consumers' familiarity with an online store' website interface significantly improves their online product brokering efficiency by reducing their information search cost and increasing their decision making satisfaction, which in turn increases consumers' repurchase intention.   For online firms who aim to lock in their customers, they should try to maintain the layout of their website and avoid any major changes. It should be noted that the lock-in through consumer learning cannot bring sustained competitive to online firms because it is not too hard for their competitors to imitate. Firms who want to recruit more customers can easily change their website to make it look similar to those well-known and successful websites so as to reduce consumers' learning cost when they switch. Therefore, online firms who want to retain their customers should keep improving the design of their website to make it more difficult for their competitors to imitate, but avoid major changes that will affect the shopping efficiency of their loyal customers.

Finally, although findings of this study prove that personalization is a powerful tool to establish and maintain strong customer store loyalty, generalized services should not be neglected. A user-friendly website interface, wide selection of products, high quality of detailed product information, reliable product delivery, and reasonable prices are also attractive to online shoppers. High quality generalized services are necessary, if not adequate, for an online store to attract and keep their customers. When a website fails to provide basic functions, customers will not want to come back no matter how fancy the personalized services are. It is very likely that personalization starts having an impact only after the quality of generalized services has reached a certain level as in the case of

Amazon.com. With limited resources, online retailers need to balance their investment in these two types of services in order to receive the optimal return.

5.8 Contributions

As one of the first empirical studies to investigate the impact of PPRs on consumer store loyalty in the online shopping environment, this study makes important contributions to the e-commerce literature. First, this study provides a theoretical framework that explains the mechanism through which PPRs improve customer store loyalty in electronic markets. Consumers incur significant amount of cognitive cost when shopping online. The joint effort of consumer learning and retailer learning can significantly improve consumer shopping efficiency, which in turn drives consumer store loyalty. This framework can be generalized to investigate the impact of personalized services in general or any form of personalized service in particular on consumer store loyalty.

Moreover, in order to create a natural setting for the subjects and at the same time manipulating the core variable of this study – the quality of PPRs, a combination of lab experiment and survey was used for data collection. As pointed out by Kumar and Benbasat (2001), empirical research about PPRs is very limited due to the difficulty of collecting data. This study provides a new and feasible data collection method for future research on PPRs.

In addition, findings of this study provide the first empirical evidence to answer the following questions: (1) Do PPRs generate any value for online consumers and retailers? (2) How is the value generated? Finally, (3) compared to other aspects of

retailers' services, how important are PPRs in building customer store loyalty online?

Answers to these questions not only help researchers better understand how PPRs

influence consumers' shopping behavior in electronic markets but also provide guidelines

for online retailers to better adjust their IT strategies to further improve customer

retention.

5.9 Future Research

Several interesting and important issues about PPRs remain to be investigated in

the future. First, how do PPRs influence consumers' product brokering efficiency when

they are completely irrelevant? In this study, a major assumption is that PPRs are not

completely irrelevant. However, this is not always true in real life and consumers receive

irrelevant PPRs from time to time. When PPRs are completely off target, consumers may

find them distracting, intrusive, and annoying. Under these circumstances, consumers'

product brokering efficiency may be even lower than when there are no recommendations

at all. Whether completely irrelevant PPRs will reduce consumer online product

brokering efficiency and produce a negative impact on consumer repurchase intention is

an important issue that should be empirically investigated in future research to improve

the effectiveness of PPRs as a customer retention strategy.

Second, how do PPRs influence consumers' purchase decisions? For online

retailers, besides customer retention, another important motivation to offer PPRs is to

increase sales. The impact of PPRs on consumers' likelihood to make unplanned

purchases such as purchasing more items (cross-sales) or purchasing more expensive

items (up-sales) is a very important and exciting area that needs more attention from researchers.

Third, this study did not distinguish two types of online shoppers – experiential shoppers vs. goal-oriented shoppers. By definition, consumers in these two groups seek different value when shopping online and this difference may moderate the relationship between their online product brokering efficiency and repurchase intention. For example, the level of input to the shopping process – time and cognitive cost – may have greater impact on consumers' repurchase intention for goal-oriented shoppers than for experiential shoppers. Moreover, consumers' online product brokering process has two types of output: the quality of purchase decisions (utilitarian value) and the fun experienced during the decision making process (hedonic value). For goal-oriented shoppers, the utilitarian value obtained from the online product brokering process may have stronger influence on their repurchase intention than the hedonic value, and it is the opposite for experiential shoppers.

Finally, how do other forms of personalized services affect consumer's online shopping efficiency? Online retailers offer personalized services in many different ways such as personalized emails and one-click-ordering system. These personalized services may influence consumers' shopping efficiency at different stages. For example, personalized emails may increase consumers' need identification efficiency, while one-click-ordering system may improve consumers' purchase efficiency. Theoretical frameworks and empirical analyses are needed for us to understand how personalization as a strategic package influences consumer shopping behavior in electronic markets.

5.10 Conclusion

Personalization has been adopted by more and more online retailers as a strategy to improve customer retention when facing increasingly intense competition in electronic markets. Personalized product recommendations (PPRs) are product recommendations that adapt to individual consumers' needs based on their preferences and taste revealed from their previous purchases and product ratings. Advances in information technologies, more specifically, the recommender systems, have made implementing PPRs much more efficient. Although one of the most important motivations for many online firms to offer PPRs is to improve customer retention, not only is empirical evidence very sparse, the limited anecdotal evidence contradictory. Building upon the household production function model in the consumer economics literature, this study develops a theoretical framework that explains the mechanism through which PPRs influence customer store loyalty in the online shopping environment.

Empirical analyses reveal that higher level of consumer input to the recommender system increases the quality of PPRs, which in turn increases consumers' online product brokering efficiency, which finally leads to higher repurchase intention. An interesting finding of this study is that higher quality PPRs increase rather than reduce consumer online product brokering cost measured using the total time expended on decision making. When the quality of PPRs improves, consumers incur lower information search cost but higher information processing cost because they have more alternatives to evaluate or the size of their consideration set increases. In the specific setting of this study, consumers' information processing cost dominates information search cost and

this is why consumers' total online product brokering cost goes up. At the expense of higher product brokering cost, consumers' product brokering quality also increases. When the quality of PPRs improves, consumers are more confident that they have made the best choice for themselves and experience more fun during the product brokering process. In other words, consumers obtain more utilitarian value as well as more hedonic value when receiving higher quality PPRs.

Although higher quality PPRs have a mixed impact on consumer online product brokering quality and cost, the results indicate that consumer repurchase intention is only significantly affected by consumer online product brokering quality but not by consumer online product brokering cost. Both consumer decision making confidence and decision making satisfaction significantly increase consumer repurchase intention. This implies that increase in product brokering quality outweighs the increase in product brokering cost and therefore, consumer product brokering efficiency – the ratio of product brokering quality to product brokering cost – increases.

This study provides one of the first empirical evidence in the literature that PPRs have the potential to significantly improve customer store loyalty online. However, the results seem inconsistent with the reality that PPRs are not perceived useful by many consumers because of poor quality (Jupiter Research 2003). Insufficient input from individual consumers is a major reason that the quality of PPRs cannot be improved. To realize the full potential of PPRs, online retailers need to offer more incentives to their customers to solicit more product ratings so that to break the vicious circle.

Personalization in general and PPRs in particular are strategies that have the potential to bring sustained competitive advantage to online retailers. Although

generalized services are still playing an important role in maintaining customers, they will not give online retailers a competitive edge in the long run. When the improvement in the quality of generalized services reaches the limit, personalization will become the only powerful weapon for online retailers to beat their competitors.

TABLE 1. SUMMARY OF MODIFICATIONS TO THE STUDY DESIGN IN PILOT STUDIES

	Measurement	Procedures
1st Round Pilot	(1) Items that measure the unfavorable repurchase intentions were dropped to shorten the experiment; (2) Total decision making time was not measured to simplify the experiment.	
2nd Round Pilot	(1) Subjective measures of consumer product category knowledge and website knowledge were collected. (2) The total number of orders placed with Amazon.com during the past six months was used to measure consumers' previous experience with Amazon.com, rather than their website knowledge.	(1) Subjects evaluated the quality of PPRs before they made the simulated purchase; (2) Experiment was conducted in two phases. Subjects' product ratings were collected in phase I. Then, I created a fake account for each subject and entered the product ratings. In phase II, subjects completed the simulated purchase in the lab.
3rd Round Pilot	(1) Total decision making time was used as an objective measure of consumers' online product brokering cost; (2) Satisfaction with the decision making process was used as an alternative measure of consumer online product brokering quality; (3) Decision making involvement was measured and used as a control variable; (4) Individual consumer characteristics such as age, gender, Internet experience, and online shopping experience were collected as control variables.	(1) Consumer input to the recommender system was only manipulated in two levels – high input (15 product ratings) vs. low input (5 product ratings); (2) All the subjects were screened first after phase I and those who rated fewer than 15 items were dropped from the sample, and the rest subjects were randomly assigned to one of the two treatment conditions; (3) Media Lab was used to collect subjects' clickstream data when they were browsing at Amazon.com so that an accurate measure of consumers' total decision making time could be obtained.
Final Study	(1) Consumers' perceived information search cost was measured; (2) Items measuring consumer decision making confidence were revised.	

TABLE 2. OPERATIONALIZATION OF RESEARCH VARIABLES

Variable	Measurement	Source
Quality of PPRs	Consumers' perceptions about how closely the recommended items match their preferences or tastes	Adapted from Adler et al. (2002), Adomavicius and Tuzhilin (2002), Geoffrion and Krishnan (2001), Kumar et al. (2000), and Tan et al. (2003)
Consumer Online Product Brokering Costs	Perceived ease of making the purchase decision	Adapted from Chatterjee and Heath (1996) and Pereira (2001)
	Time expended to reach the purchase decision	Adapted from Haubl and Trifts (2000)
	Perceived ease of information search	Adapted from Chatterjee and Heath (1996) and Pereira (2001)
Consumer Online Product Brokering Quality	Confidence that right items have been selected	Adapted from Bearden, et al. (2001) and Pereira (2001)
	Satisfaction with the decision making process	Adapted from Kourilsky and Murray (1981)
Consumer Product Category Knowledge	Subjective evaluation of familiarity with DVDs	Adapted from Cowley and Mitchell (2003)
	Number of items watched out of the top seller list	Self-developed
Consumer Website Knowledge	Subjective evaluation of familiarity with Amazon.com's website	Adapted from Cowley and Mitchell (2003)
Consumer Store Loyalty	Likelihood of purchasing from Amazon.com again	Adapted from Zeithaml, et al. (1996)
Product Selection	Perceived selection of DVD items	Adapted from Wolfinbarger and Gilly (2003)
Website Usability	Perceived ease of navigating Amazon.com's website	Adapted from McKinney, Yoon, and Zahedi (2002)
Quality of Detailed Product Information	Perceived usefulness of detailed product information	Adapted from McKinney, Yoon, and Zahedi (2002)
Decision Making Involvement	Importance of the purchase decision to consumers	Adapted from Pham (1996)
Purchase Efficiency	Perceived ease of checking out the items at the online store	Self-developed
Delivery Efficiency	Perceived ease of getting the right items delivered on time and in good shape	Self-developed
Post-sales Efficiency	Perceived ease of returning items to the online store	Self-developed
Price Perception	Consumers' perception about whether the prices charged by Amazon.com are reasonable.	Adapted from Bei and Chiao (2001)
Previous Experience with Amazon.com	Whether the subject has shopped at Amazon.com or not	Self-developed

TABLE 3. LIST OF MEASUREMENT ITEMS

Construct	Items
Quality of PPRs	PPR1: In general, most items on this list match my preferences very well. PPR2: In general, most items on this list fit my tastes very well. PPR3: In general, most items on this list are interesting to me. PPR4: I would like to buy almost all these items if there is no budget constraint. PPR5: They are exactly what I am looking for. PPR6: I want to own all of them.
Ease of Decision Making	DMES1: It was very easy for me to make this purchase decision. DMES2: I had no difficulty deciding which item would be best for me. DMES3 Making this purchase decision was an easy task for me.
Ease of Information Search	INFSR1: I had no problem locating the items I was interested in at Amazon.com. INFSR2: It was very easy for me to locate the items I was interested in at Amazon.com. INFSR3: Locating the items I was interested in at Amazon.com was very easy.
Decision Making Confidence	DMCNF1: I have picked the items that best fit my taste among all DVDs available at Amazon.com. DMCNF2: I have selected the items I like the most among all DVDs available at Amazon.com. DMCNF3: These two items are my favorite among all DVDs available at Amazon.com. DMCNF4: I would definitely choose the same items if I were given another chance. DMCNF5: I am very satisfied with the two items I have picked for myself. DMCNF6: I am very happy that I have picked these two items.
Decision Making Satisfaction	DMST1: I have truly enjoyed the decision making process. DMST2: The decision making process was fun to me. DMST3: I am very happy with the decision making process. DMST4: The decision making process was very enjoyable.
Repurchase Intention	REPUR1: I will consider Amazon.com the first choice to buy similar products in the future. REPUR2: I will buy more similar products at Amazon.com in the future. REPUR3: I will come back to Amazon.com to buy similar products in the future.
Product Category Knowledge (Subjective Measure)	PRDKN1: I watch a lot of TV and/or movies in my spare time. PRDKN2: I know almost all popular TV shows and/or movies. PRDKN3: I can name many Hollywood actors and directors.
Website Knowledge	WBKN1: I am very familiar with Amazon.com's website. WBKN2: I am very good at using all kinds of tools to perform various purchase-related tasks at Amazon.com. WBKN3: I always know where I can find the products/information I am looking for at Amazon.com's website. WBKN4: I visit Amazon.com very often. WBKN5: I have been to Amazon.com many times.

Product Selection	PRDSL1: This website had a good selection of DVDs. PRDSL2: This website had a wide variety of DVDs that interest me. PRDSL3: I could find any DVDs I like on this website.
Website Usability	DEGN1: The website was very user-friendly. DEGN2: The website was easy to use. DEGN3: The website was well organized. DEGN4: The website was easy to navigate.
Quality of Detailed Product Information	PRDINF1: The detailed product information was very helpful. PRDINF2: The detailed product information was very useful. PRDINF3: The detailed product information was very informative.
Decision Making Involvement	DMINV1: It is very important for me to pick the right items for myself. DMINV2: I was very motivated to reach a good purchase decision. DMINV3: I really want to pick the right items for myself.
Expected Purchase Efficiency	PURCH1: It should be very easy to check out these items. PURCH2: The whole process should be very straightforward. PURCH3: I will have no difficulty checking out these items. PURCH4: I will not have any problem checking out these items.
Expected Delivery Efficiency	DELIV1: I should have no problem receiving the right items on time. DELIV2: I am very sure that I will receive the right items on time. DELIV3: I am very confident that I will receive the right items on time.
Expected Post-sales Efficiency	RETRN1: I will have no problem returning the items to Amazon.com for a refund or replacement. RETRN2: It should be very easy to return the items to Amazon.com for a refund or replacement. RETRN3: It should be very convenient to return the items to Amazon.com for a refund or replacement.
Price Perception	PRICE1: The prices charged by Amazon.com for these two items are very reasonable. PRICE2: Amazon.com is offering a good deal on these two DVD items. PRICE3: Amazon.com is offering the lowest prices for these two DVD items.

TABLE 4. SAMPLE DESCRIPTIVE STATISTICS (N=253)

Variable	Minimum	Maximum	Mean	Standard Deviation
Website Knowledge	1	7	4.11	1.39
Product Knowledge	1	7	4.70	1.44
Quality of PPRs	1	7	4.38	1.73
Decision Making Time (seconds)	18	1082	314.65	211.98
Ease of Decision Making	2	7	5.02	1.49
Ease of Information Search	1	7	4.12	1.32
Decision Making Satisfaction	2	7	4.61	1.67
Decision Making Involvement	1.33	7	4.93	1.57
Decision Making Confidence	1.33	7	4.98	1.27
Website Usability	1.33	7	5.06	1.31
Quality of Product Information	1	7	4.82	1.38
Product Selection	1	7	5.11	1.58
Purchase Efficiency	1.67	7	4.96	1.85
Delivery Efficiency	1	7	5.03	1.45
Post-sales Efficiency	1	7	4.45	1.58
Price Perception	1	7	4.80	1.43
Repurchase Intention	1	7	4.58	1.53
Number of Items Watched	15	134	36.01	17.01
Previous Experience (1=purchase before)	0	1	.61	.48
Gender (1=female)	0	1	.43	.49
Age	18	28	20.63	1.50
Internet Experience (years)	3	10	7.32	1.79

TABLE 5. FACTOR ANALYSIS RESULTS (N=253)

	WBKN	PRDKN	PPR	DMES	INFSR	DMST	DMINV	DMCNF	DEGN	PRDINF	PRDSL	PURCH	DELIV	RETRN	PRICE	REPUR
WBKN1	**[0.84]**	0.10	-0.07	0.06	-0.01	0.10	0.07	0.07	-0.04	0.07	0.09	0.13	0.04	0.00	-0.08	0.08
WBKN2	**[0.80]**	0.10	0.00	0.01	0.01	0.14	0.09	0.12	-0.12	0.08	0.15	0.14	0.10	0.10	-0.05	0.00
WBKN3	**[0.84]**	0.06	0.05	0.06	0.08	0.07	0.07	0.02	0.05	0.08	0.08	0.11	0.07	0.12	0.04	0.06
WBKN4	**[0.63]**	0.01	0.22	0.09	0.17	0.08	0.03	-0.03	0.33	0.10	-0.09	0.01	0.11	0.08	0.14	0.16
WBKN5	**[0.77]**	0.01	0.10	0.05	0.21	0.01	0.14	-0.03	0.29	0.07	0.03	-0.03	0.10	0.05	0.06	0.10
PRDKN1	0.07	**[0.85]**	0.04	0.03	-0.01	0.06	-0.04	0.06	0.04	0.00	0.09	0.05	-0.04	0.02	0.06	0.03
PRDKN2	0.05	**[0.89]**	0.10	-0.01	-0.02	0.05	-0.01	-0.01	0.15	0.03	0.03	0.05	0.05	0.02	-0.02	0.02
PRDKN3	0.11	**[0.82]**	0.04	0.10	-0.02	0.02	0.16	-0.02	0.07	0.07	0.07	-0.01	0.11	0.03	0.05	-0.01
PPR1	0.10	0.01	**[0.79]**	-0.11	0.07	-0.04	0.06	0.10	0.06	0.00	0.11	0.13	-0.02	0.03	0.06	0.02
PPR2	0.08	0.01	**[0.82]**	-0.03	0.13	0.03	0.02	0.22	0.01	0.08	0.10	0.11	0.06	0.04	0.08	0.10
PPR3	0.02	0.06	**[0.82]**	-0.07	0.12	0.04	0.07	0.13	0.14	0.03	0.14	0.11	0.00	-0.03	0.04	0.16
PPR4	-0.03	0.02	**[0.82]**	-0.06	0.18	0.15	0.04	-0.02	0.06	0.06	0.03	0.00	0.00	0.01	0.02	0.03
PPR5	0.03	0.00	**[0.86]**	-0.15	0.09	0.13	0.02	0.10	-0.04	0.05	-0.02	-0.01	-0.03	0.15	0.09	0.01
PPR6	0.01	0.15	**[0.83]**	-0.08	0.13	0.13	0.07	0.02	-0.03	0.09	0.00	-0.06	0.05	0.05	0.00	0.01
DMES1	0.11	0.10	-0.16	**[0.80]**	-0.01	0.06	0.08	0.11	0.15	0.01	0.10	0.08	0.08	0.04	0.07	-0.05
DMES2	0.05	-0.01	-0.14	**[0.85]**	0.08	0.06	0.05	0.15	0.09	0.11	0.04	0.18	0.08	0.04	0.04	0.06
DMES3	0.06	0.05	-0.22	**[0.81]**	0.13	0.08	0.12	0.08	0.17	0.05	0.10	0.12	0.08	0.05	0.03	0.07
INFSR2	0.12	-0.03	0.31	0.05	**[0.85]**	0.14	0.07	0.13	0.07	0.07	0.09	0.14	0.06	0.09	-0.01	0.03
INFSR1	0.14	-0.04	0.35	0.10	**[0.83]**	0.14	0.07	0.14	0.13	0.07	0.11	0.10	0.07	0.07	-0.05	0.05
INFSR3	0.15	-0.01	0.31	0.08	**[0.83]**	0.20	0.02	0.09	0.09	0.11	0.08	0.14	0.04	0.09	0.01	0.03
DMST1	0.10	-0.02	0.15	0.10	0.19	**[0.74]**	0.14	0.22	0.25	0.11	0.05	0.19	0.03	0.17	0.12	0.14
DMST2	0.15	0.04	0.14	0.02	0.15	**[0.80]**	0.18	0.19	0.21	0.14	0.07	0.14	0.09	0.14	0.08	0.14
DMST3	0.12	0.10	0.16	0.14	0.11	**[0.78]**	0.19	0.22	0.16	0.06	0.08	0.16	0.10	0.11	0.10	0.14
DMST4	0.14	0.09	0.14	0.05	0.14	**[0.82]**	0.16	0.23	0.13	0.16	0.07	0.11	0.12	0.09	0.09	0.13
DMINV1	0.07	0.06	0.09	0.15	0.07	0.21	**[0.75]**	0.23	0.13	0.09	0.12	0.19	0.10	0.01	0.10	0.12
DMINV2	0.20	0.04	0.16	0.05	0.03	0.22	**[0.77]**	0.17	0.09	0.12	0.05	0.12	0.14	0.09	0.06	0.14
DMINV3	0.17	0.03	0.07	0.10	0.06	0.16	**[0.82]**	0.23	0.09	0.08	0.07	0.25	0.09	0.07	0.03	0.06
DMCNF1	0.07	0.03	0.12	0.06	0.01	0.20	0.07	**[0.77]**	0.00	-0.03	0.07	0.09	0.09	0.07	0.07	0.09
DMCNF2	-0.01	0.06	0.09	0.07	-0.05	0.08	0.00	**[0.83]**	0.04	0.10	0.05	0.12	0.16	0.04	-0.08	0.03
DMCNF3	0.00	-0.04	0.12	0.03	-0.02	0.06	0.01	**[0.80]**	0.13	0.15	-0.03	0.00	-0.02	0.12	0.01	0.03
DMCNF4	0.05	-0.02	0.10	0.01	0.07	0.10	0.11	**[0.86]**	0.07	0.08	-0.01	0.02	-0.03	0.12	0.07	0.01
DMCNF5	0.06	0.04	0.05	0.15	0.22	0.12	0.24	**[0.76]**	0.16	0.02	0.13	-0.01	0.09	0.06	0.12	0.05
DMCNF6	0.03	0.00	0.07	0.12	0.22	0.12	0.23	**[0.77]**	0.13	0.02	0.16	0.07	0.09	0.02	0.09	0.09
DEGN1	0.14	0.11	0.00	0.17	0.08	0.19	0.10	0.14	**[0.70]**	0.15	0.20	0.25	0.05	0.10	0.14	0.08
DEGN2	0.09	0.12	0.05	0.14	0.13	0.24	0.13	0.16	**[0.75]**	0.18	0.17	0.21	0.16	0.10	0.06	0.08
DEGN3	0.06	0.11	0.07	0.14	0.07	0.15	0.05	0.18	**[0.78]**	0.16	0.17	0.24	0.08	0.17	0.06	0.13
DEGN4	0.06	0.11	0.06	0.16	0.07	0.18	0.10	0.19	**[0.77]**	0.18	0.20	0.23	0.13	0.12	0.07	0.08
PRDINF1	0.18	0.08	0.13	0.00	0.06	0.10	0.08	0.14	0.23	**[0.78]**	0.16	0.14	0.09	0.11	0.17	0.13
PRDINF2	0.12	0.02	0.11	0.10	0.11	0.11	0.08	0.12	0.18	**[0.84]**	0.10	0.15	0.16	0.10	0.12	0.14
PRDINF3	0.16	0.05	0.12	0.12	0.10	0.20	0.15	0.13	0.16	**[0.78]**	0.15	0.17	0.15	0.08	0.11	0.12
PRDSL1	0.16	0.12	0.13	0.06	0.13	0.08	0.12	0.09	0.28	0.15	**[0.75]**	0.18	0.06	0.07	0.21	0.07
PRDSL2	0.18	0.09	0.17	0.13	0.12	0.14	0.10	0.10	0.25	0.18	**[0.76]**	0.20	0.12	0.05	0.14	0.12
PRDSL3	0.05	0.11	0.19	0.17	0.09	0.06	0.05	0.17	0.19	0.15	**[0.69]**	0.28	0.17	0.08	0.05	0.12
PURCH1	0.12	0.03	0.07	0.16	0.04	0.08	0.17	0.08	0.16	0.13	0.19	**[0.78]**	0.13	0.12	0.16	0.05
PURCH2	0.10	0.09	0.08	0.07	0.08	0.14	0.15	0.11	0.19	0.06	0.11	**[0.79]**	0.18	0.10	0.06	0.10
PURCH3	0.10	0.01	0.07	0.12	0.14	0.13	0.14	0.05	0.22	0.13	0.14	**[0.82]**	0.20	0.08	0.09	0.12
PURCH4	0.12	-0.02	0.10	0.13	0.14	0.17	0.10	0.04	0.20	0.13	0.11	**[0.82]**	0.20	0.07	0.08	0.10
DELIV1	0.19	0.09	-0.06	0.11	0.04	0.11	0.13	0.16	0.15	0.04	0.14	0.29	**[0.73]**	0.15	0.14	0.12
DELIV2	0.16	0.06	0.04	0.10	0.08	0.10	0.12	0.14	0.11	0.19	0.07	0.24	**[0.83]**	0.19	0.10	0.11

TABLE 6. RESULTS OF CONFIRMATORY FACTOR ANALYSIS WITH LISREL (N=253)

Construct	Items	Standardized Parameter Estimate	T-value
Website Knowledge	WBKN3	.72	11.84
	WBKN4	.81	13.57
	WBKN5	.84	14.04
Product Category Knowledge	PRDKN2	.83	13.48
	PRDKN3	.87	14.39
Quality of PPRs	PPR1	.77	12.63
	PPR2	.83	14.03
	PPR3	.79	12.95
Ease of Decision Making	DMES1	.79	12.11
	DMES2	.87	14.68
	DMES3	.81	13.60
Ease of Information Search	INFSR1	.78	11.62
	INFSR2	.89	14.19
	INFSR3	.81	13.34
Decision Making Satisfaction	DMST1	.85	14.65
	DMST2	.79	13.19
	DMST3	.78	12.76
Decision Making Involvement	DMINV1	.75	12.06
	DMINV2	.84	13.10
	DMINV3	.77	12.14
Decision Making Confidence	DMCNF1	.88	13.97
	DMCNF2	.89	14.18
	DMCNF3	.77	12.86
Website Usability	DEGN1	.80	13.14
	DEGN2	.78	12.17
	DEGN3	.75	11.95

Quality of Detailed Product Information	PRDINF1	.73	12.73
	PRDINF2	.76	12.88
	PRDINF3	.68	11.46
Product Selection	PRDSL1	.71	11.95
	PRDSL2	.75	12.17
	PRDSL3	.74	12.06
Purchase Efficiency	PURCH1	.80	13.07
	PURCH2	.69	11.52
	PURCH3	.73	12.85
Delivery Efficiency	DELIV1	.87	13.77
	DELIV2	.73	12.02
	DELIV3	.75	12.25
Post-sales Efficiency	RETRN1	.86	13.70
	RETRN2	.76	12.08
	RETRN3	.77	12.33
Price Perception	PRICE1	.89	14.09
	PRICE2	.72	12.07
	PRICE3	.80	13.20
Repurchase Intention	REPUR1	.71	11.88
	REPUR2	.85	13.45
	REPUR3	.78	12.47

TABLE 7. GOODNESS-OF-FIT INDICES OF CONFIRMATORY FACTOR ANALYSIS

Index	Lisrel Output	Desired Levels[a]
χ^2	1037.89	smaller
df	914	---
χ^2/df	1.14	<3.0
GFI	.85	>.9
AGFI	.82	>.8
Standardized RMR	.04	<.05
RMSEA	.06	.05 - .08
NFI	.91	>.9
CFI	.95	>.9

[a] – see Bassellier, Benbasat, and Reich (2003).

TABLE 8. INTER-CONSTRUCT CORRELATIONS (N=253)

	DMES	INFSR	DMST	DMCNF	WBKN	PRDKN	PPR	DMINV	DEGN	PRDINF	PRDSL	PURCH	DELIV	RETRN	PRICE	REPUR
DMES	**.86**															
INFSR	.17	**.97**														
DMST	.28	.46	**.94**													
DMCNF	.20	.40	.40	**.86**												
WBKN	.20	.37	.36	.10	**.86**											
PRDKN	-.13	-.23	-.16	-.05	-.18	**.90**										
PPR	-.24	.48	.31	.26	.23	-.11	**.90**									
DMINV	-.31	.10	.25	.37	.33	-.17	.26	**.91**								
DEGN	.41	.36	.57	.32	.38	-.26	.24	.44	**.93**							
PRDINF	.26	.34	.47	.29	.39	-.18	.28	.41	.54	**.93**						
PRDSL	.33	.39	.44	.28	.36	-.26	.36	.41	.40	.42	**.92**					
PURCH	.36	.33	.47	.24	.32	-.16	.26	.50	.58	.46	.57	**.92**				
DELIV	.34	.27	.42	.30	.37	-.20	.16	.44	.47	.49	.46	.59	**.93**			
RETRN	.19	.28	.43	.29	.31	-.13	.18	.29	.40	.36	.32	.36	.44	**.94**		
PRICE	.17	.11	.34	.18	.19	-.11	.21	.27	.34	.37	.38	.33	.36	.42	**.89**	
REPUR	.18	.26	.52	.31	.39	-.12	.32	.44	.45	.49	.43	.44	.47	.41	.58	**.95**

WBKN – Website Knowledge; PRDKN – Product Category Knowledge; PPR – Quality of PPRs; DMES – Ease of Decision Making; INFSR – Ease of Information Search; DMST – Decision Making Satisfaction; DMINV – Decision Making Involvement; DMCNF – Decision Making Confidence; DEGN – Website Usability; PRDINF - Quality of Detailed Product Information; PRDSL – Product Selection; PURCH – Purchase Efficiency; DELIV – Delivery Efficiency; RETRN – Post-sales Efficiency; PRICE – Price Perception; REPUR – Repurchase Intention

TABLE 9. RELIABILITY OF MEASUREMENT SCALES (N=253)

Construct	Cronbach's Alpha (Number of Items)
Quality of PPRs	.89(3)
Website Knowledge	.85 (3)
Product Category Knowledge	.82 (2)
Website Usability	.92 (3)
Product Information Quality	.94 (3)
Product Selection	.89 (3)
Decision Making Involvement	.81 (3)
Ease of Decision Making	.88 (3)
Ease of Information Search	.93 (3)
Decision Making Confidence	.85 (3)
Decision Making Satisfaction	.94 (3)
Purchase Efficiency	.92 (3)
Delivery Efficiency	.89 (3)
Post-sales Efficiency	.93 (3)
Repurchase Intention	.90 (3)
Price Perception	.89 (3)

TABLE 10. ANOVA RESULTS (DEPENDENT VARIABLE – QUALITY OF PPRS) (N=253)

Group	Number of Items Rated	Number of Subjects	Mean (Std)	F Statistics
Low Input	5	127	4.03 (1.23)	52.31 ***
High Input	15	126	5.11 (1.15)	

* significant at $\alpha = 0.05$ ** significant at $\alpha = 0.01$ *** significant at $\alpha = 0.001$

TABLE 11. PLS OUTER MODEL LOADINGS

Construct	Indicator	Loading
Website Knowledge	WBKN3	.84
	WBKN4	.89
	WBKN5	.87
Product Category Knowledge	PRDKN2	.90
	PRDKN3	.93
Quality of PPRs	PPR1	.88
	PPR2	.94
	PPR3	.91
Ease of Decision Making	DMES1	.86
	DMES2	.90
	DMES3	.91
Ease of Information Search	INFSR1	.93
	INFSR2	.96
	INFSR3	.97
Decision Making Satisfaction	DMST1	.94
	DMST2	.95
	DMST3	.93
Decision Making Involvement	DMINV1	.91
	DMINV2	.89
	DMINV3	.94
Decision Making Confidence	DMCNF1	.87
	DMCNF2	.90
	DMCNF3	.85
Website Usability	DEGN1	.91
	DEGN2	.95
	DEGN3	.92
Quality of Detailed Product Information	PRDINF1	.92
	PRDINF2	.95
	PRDINF3	.95

Product Selection	PRDSL1	.90
	PRDSL2	.95
	PRDSL3	.88
Purchase Efficiency	PURCH1	.91
	PURCH2	.91
	PURCH3	.94
Delivery Efficiency	DELIV1	.90
	DELIV2	.96
	DELIV3	.95
Post-sales Efficiency	RETRN1	.91
	RETRN2	.96
	RETRN3	.93
Price Perception	PRICE1	.91
	PRICE2	.94
	PRICE3	.86
Repurchase Intention	REPUR1	.92
	REPUR2	.97
	REPUR3	.97

TABLE 12. RESULTS OF PLS ANALYSIS: PATH COEFFICIENTS (N=253)

Dependent Variable	Independent Variable	Path Coefficients
Decision Making Time	Website Knowledge	.09
	Product Category Knowledge	.31*
	Quality of PPRs	.21*
	Product Category Knowledge X Quality of PPRs	.05
	Decision Making Involvement	.08
	Website Usability	-.27*
	Product Selection	.33*
	Quality of Detailed Product Information	.11
	Age	-.12*
	Gender	-.07
	Internet Experience	-.24*
Ease of Decision Making	Website Knowledge	.06
	Product Category Knowledge	-.01
	Quality of PPRs	-.36*
	Product Category Knowledge X Quality of PPRs	-.07
	Decision Making Involvement	-.19*
	Website Usability	.26*
	Product Selection	.18*
	Quality of Detailed Product Information	.03
	Age	-.09
	Gender	.06
	Internet Experience	-.04
Ease of Information Search	Website Knowledge	.19*
	Product Category Knowledge	.11*
	Quality of PPRs	.35*
	Product Category Knowledge X Quality of PPRs	-.06
	Website Usability	.12*
	Product Selection	.11
	Quality of Detailed Product Information	.06
	Age	-.03
	Gender	-.07
	Internet Experience	-.03

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Decision Making Confidence	Website Knowledge	-.11
	Product Category Knowledge	.06
	Quality of PPRs	.15*
	Product Category Knowledge X Quality of PPRs	.03
	Decision Making Involvement	.25*
	Website Usability	.17*
	Product Selection	.05
	Quality of Detailed Product Information	.10
	Age	.01
	Gender	.11
	Internet Experience	-.06
Decision Making Satisfaction	Website Knowledge	.11*
	Product Category Knowledge	.01
	Quality of PPRs	.24*
	Product Category Knowledge X Quality of PPRs	.10
	Website Usability	.30*
	Product Selection	.05
	Quality of Detailed Product Information	.15*
	Age	.03
	Gender	.07
	Internet Experience	-.03
Repurchase Intention	Decision Making Time	.05
	Ease of Decision Making	-.04
	Ease of Information Search	.02
	Decision Making Confidence	.19*
	Decision Making Satisfaction	.24*
	Purchase Efficiency	.08
	Delivery Efficiency	.14*
	Post-sales Efficiency	.01
	Price Perception	.41*
	Age	.05
	Gender	.01
	Internet Experience	.04
	Previous Experience	.12*

* significant at $\alpha = 0.05$

TABLE 13. PLS RESULTS SUMMARY

Variable	Product Brokering Cost			Product Brokering Quality		Store Loyalty
	DM[a] Time	Ease of DM[a]	Ease of Info Search	DM[a] Confidence	DM[a] Satisfaction	Repurchase
Website Know			(+)		(+)	---
Product Know	(+)		(-)			---
Quality of PPRs	(+)	(-)	(+)	(+)	(+)	---
Web Usability	(-)	(+)	(+)	(+)	(+)	---
Product Selection	(-)	(+)				---
Product Info					(+)	---
DM[a] Involvement		(-)		(+)		---
PPRs X Prod Know						
DM[a] Time	---	---	---	---	---	
Ease of DM[a]	---	---	---	---	---	
Ease of Info Search	---	---	---	---	---	
DM[a] Confidence	---	---	---	---	---	(+)
DM[a] Satisfaction	---	---	---	---	---	(+)
Purchase Efficiency	---	---	---	---	---	
Delivery Efficiency	---	---	---	---	---	(+)
Post-sales Efficiency	---	---	---	---	---	
Price Perception	---	---	---	---	---	(+)
Previous Experience	---	---	---	---	---	(+)
Age	(-)					
Gender						
Internet Experience	(-)					

a - Decision Making

TABLE 14. HYPOTHESIS TESTING SUMMARY

Hypotheses		Supported	Significant in the Opposite Direction
H1a: The quality of PPRs has a negative effect on consumers' online product brokering cost.	Total Decision Making Time		X
	Ease of Decision Making		X
	Ease of Information Search	X	
H1b: The quality of PPRs has a positive effect on consumers' online product brokering quality.	Decision Making Confidence	X	
	Decision Making Satisfaction	X	
H2a: Consumers' product category knowledge has a negative effect on their online product brokering cost.	Total Decision Making Time		X
	Ease of Decision Making		
	Ease of Information Search		X
H2b: Consumers' product category knowledge has a positive effect on their online product brokering quality.	Decision Making Confidence		
	Decision Making Satisfaction		
H3a: Consumers' website knowledge has a negative effect on their online product brokering cost.	Total Decision Making Time		
	Ease of Decision Making		
	Ease of Information Search	X	
H3b: Consumers' website knowledge has a positive effect on their online product brokering quality.	Decision Making Confidence		
	Decision Making Satisfaction	X	
H4a: The effect of the quality of PPRs on consumers' online product brokering cost is stronger for consumers with lower product category knowledge.	Total Decision Making Time		
	Ease of Decision Making		
	Ease of Information Search		
H4b: The effect of the quality of PPRs on consumers' online product brokering quality is stronger for consumers with lower product category knowledge.	Decision Making Confidence		
	Decision Making Satisfaction		
H5a: Consumers' online product brokering cost has a negative effect on their store loyalty.	Total Decision Making Time		
	Ease of Decision Making		
	Ease of Information Search		
H5b: Consumers' online product brokering quality has a positive effect on their store loyalty.	Decision Making Confidence	X	
	Decision Making Satisfaction	X	

FIGURE 1. MAP OF LITERATURE REVIEW

Personalization and Recommender Systems

Various Forms of Personalization

↓

Previous Studies on Personalization

↓

Personalized Product Recommendations (PPRs)

Lack of empirical research about the impact of PPRs on customer store loyalty.

Customer Loyalty

Customer Brand Loyalty

↓

Customer Store Loyalty

↓

Customer Satisfaction-Store Loyalty Framework

Alternative framework is needed due to limitations of the customer satisfaction-store loyalty framework.

Alternative Framework

Customer Value

↓

Household Production Function

Customer store loyalty is driven by high online shopping efficiency, which can be achieved through a learning process.

Consumer Learning

↓

Retailer Learning

FIGURE 2. CONCEPTUAL MODEL
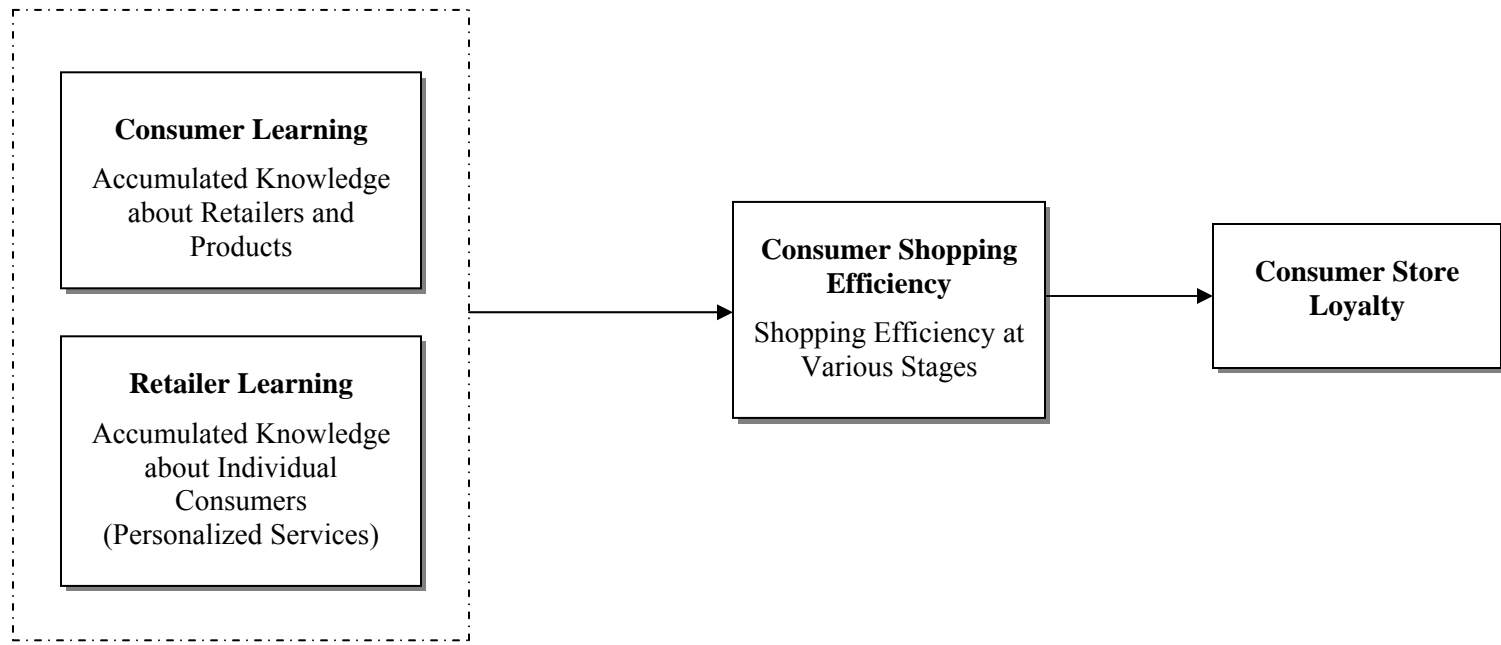
FIGURE 3. RESEARCH MODEL
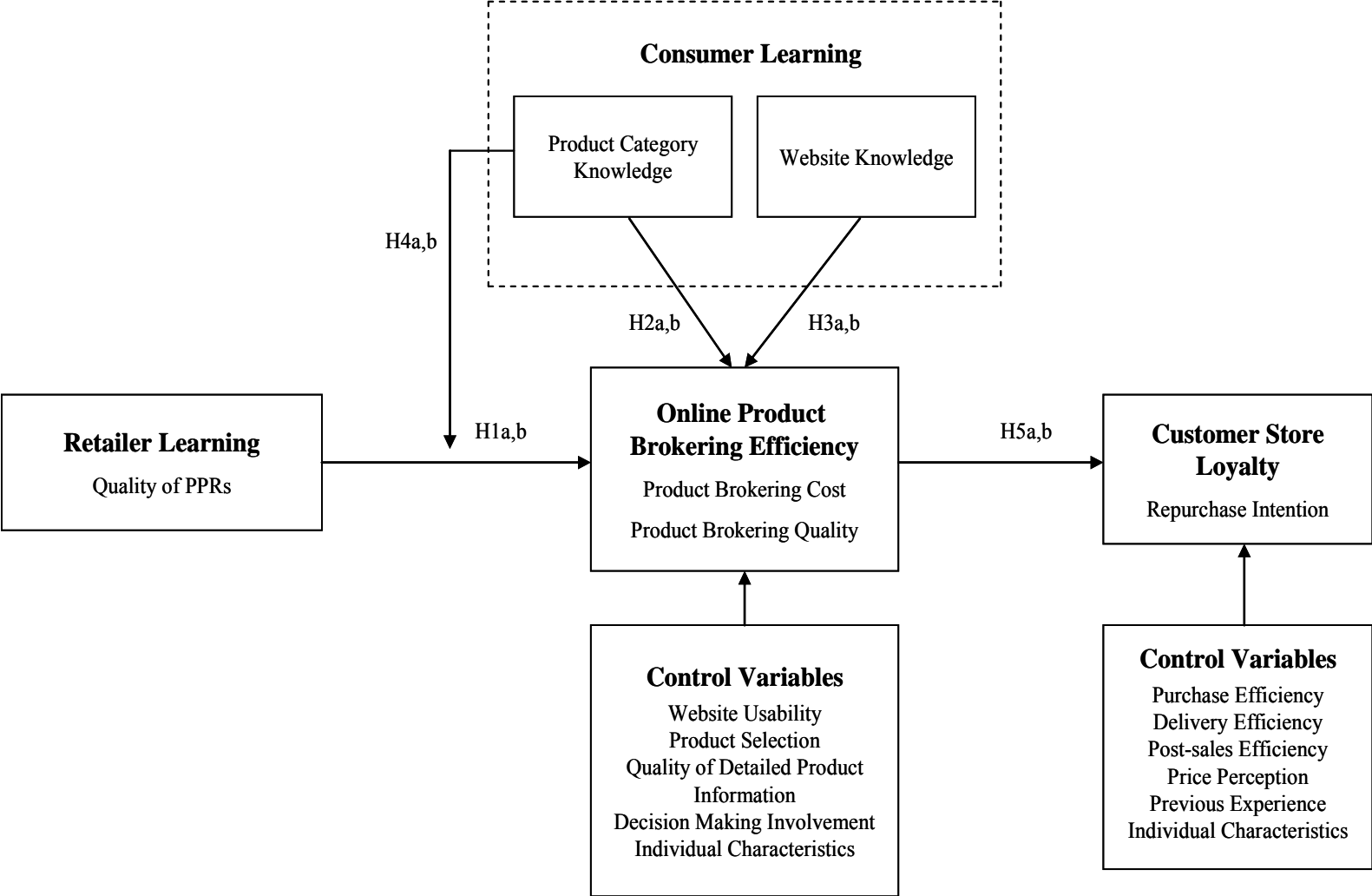
FIGURE 4. EXPERIMENTAL PROCEDURES

Phase I

Step 1: Rated top seller DVDs on paper.

The researcher:
(1) Dropped subjects who have rated fewer than 15 items;
(2) Randomly assigned subjects to two treatment conditions;
(3) Created a fake account for each subject at Amazon.com and entered their product ratings.

Phase II
(Two days later)

Step 2: Logged on to Amazon.com as a new customer with the assigned fake email and password;

Step 3: Evaluated their product category and website knowledge;

Step 4: Picked two DVDs for themselves;

Step 5: Evaluated the ease and quality of product brokering;

Step 6: Evaluated website usability, product selection, and the quality of detailed product information;

Step 7: Evaluated expected purchase efficiency, product delivery efficiency, and post-sales service efficiency;

Step 8: Indicated their repurchase intention.

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FIGURE 5. OVERVIEW OF MODEL ESTIMATION RESULTS WITH PLS [a] (N=253)
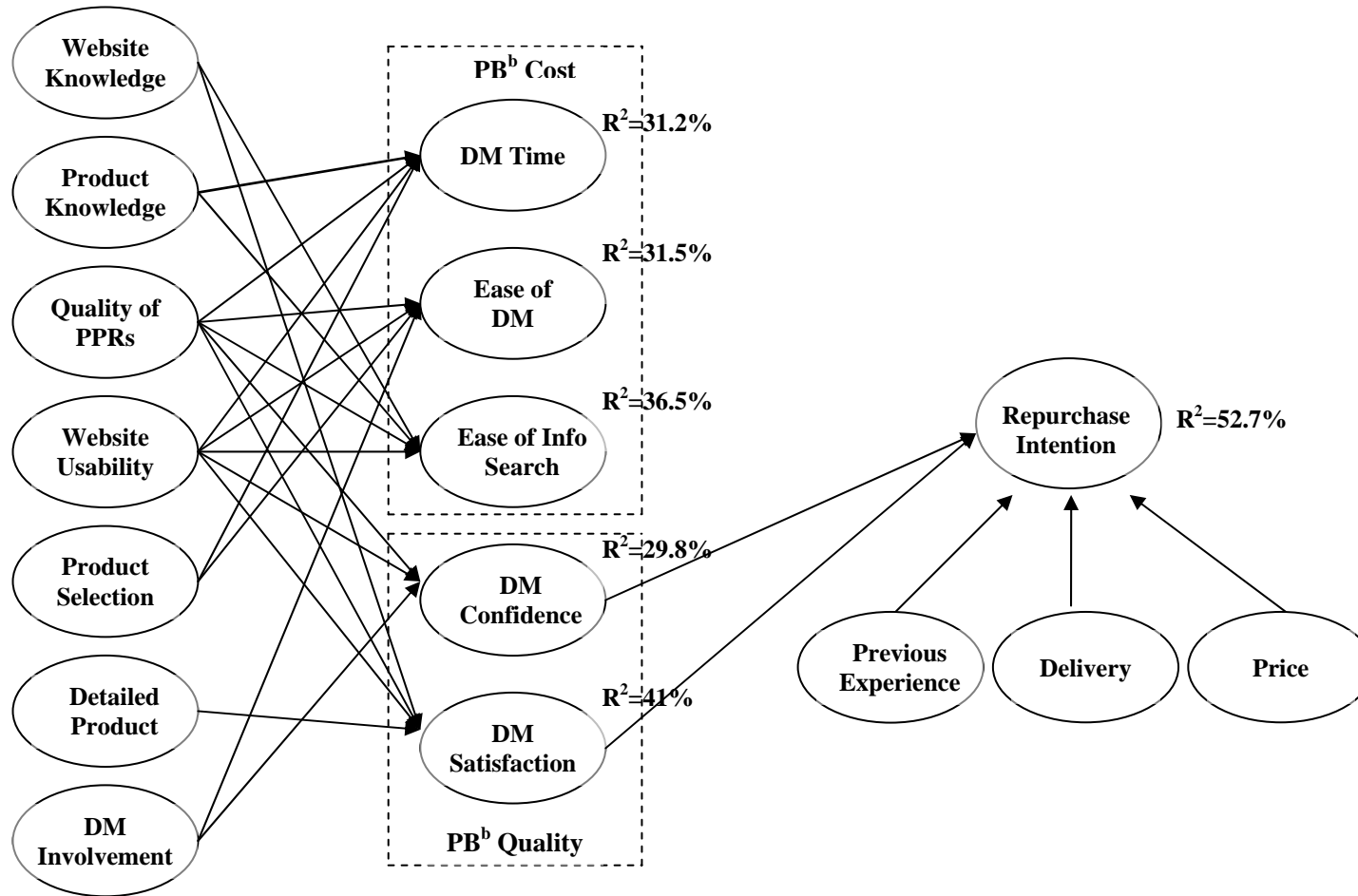
a – Only significant paths are shown in the model
b – Product Brokering

FIGURE 6. MODEL ESTIMATION RESULTS WITH PLS [a] (CORE MODEL) (N=253)

PB[b] Cost

Website Knowledge

Product Knowledge

Quality of PPRs

DM Time R^2=31.2%

Ease of DM R^2=31.5%

Ease of Info Search R^2=36.5%

DM Confidence R^2=29.8%

DM Satisfaction R^2=41%

Repurchase Intention R^2=52.7%

PB[b] Quality

(+) (+) (-) (+) (-) (+) (+) (+) (+) (+) (+) (+)

[a] – Only significant paths are shown in the model
[b] – Product Brokering

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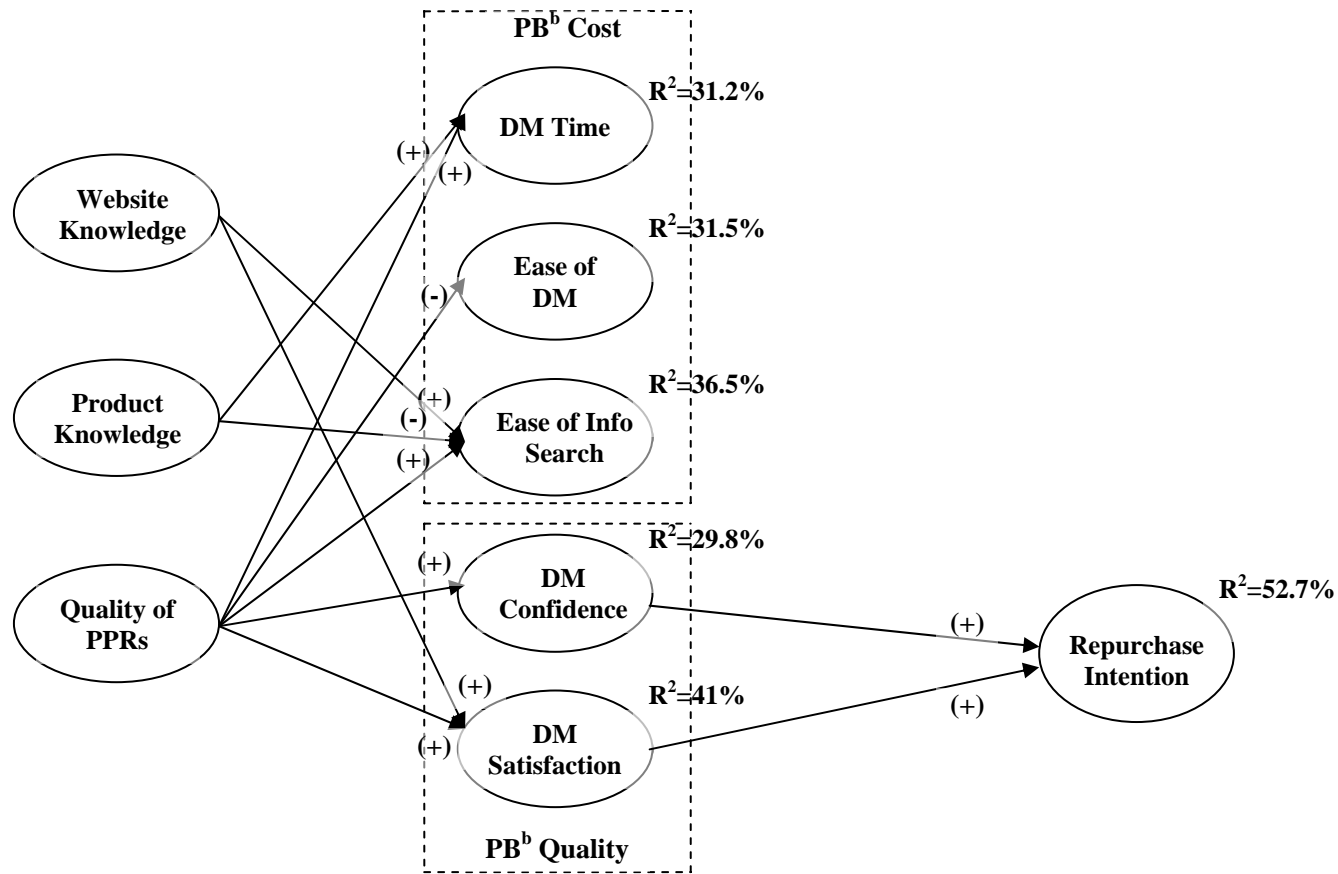
Appendix 1. Operationalization of Research Variables in Pilot Studies

Variable	1st Round Pilot	2nd Round Pilot	Pooled Sample	3rd Round Pilot
	PPR1	PPR1	PPR1	PPR1
	PPR2	PPR2	PPR2	PPR2
Quality of PPRs	PPR3 - dropped	PPR3	PPR3	PPR3
				PPR4
	---	---	---	PPR5
				PPR6
	DMES1	DMES1	DMES1	DMES1
Ease of Decision Making	DMES2	DMES2	DMES2	DMES2
	DMES3	DMES3	DMES3	DMES3
Total Decision Making Time	---	---	---	Total Decision Making Time
	DMCNF1	DMCNF1	DMCNF1	DMCNF1
	DMCNF2	DMCNF2	DMCNF2	DMCNF2
Decision Making Confidence	DMCNF3	DMCNF3 - dropped	DMCNF3 - dropped	DMCNF3
	DMCNF4	DMCNF4 - dropped	DMCNF4 - dropped	DMCNF4 - dropped
	---	---	---	DMCNF5
				DMCNF6
				DMST1
Decision Making Satisfaction	---	---	---	DMST2
				DMST3
				DMST4 - dropped
	REPUR1	REPUR1	REPUR1	REPUR1
Repurchase Intention	REPUR2	REPUR2	REPUR2	REPUR2
	REPUR3	REPUR3 - dropped	REPUR3	REPUR3
	REPUR4 - dropped	REPUR4 - dropped	REPUR4	REPUR4 - dropped
	Number of items watched out of the first 30 top sellers	Number of items watched out of the first 30 top sellers	Number of items watched out of the first 30 top sellers	Number of items watched out of 100 top sellers
Product Category Knowledge		PRDKN1		PRDKN1
	---	PRDKN2	---	PRDKN2
		PRDKN3		PRDKN3
	Number of orders placed in the past six months	---	Number of orders placed in the past six months	---
Website Knowledge		WBKN1		WBKN1
		WBKN2		WBKN2
	---	WBKN3	---	WBKN3
				WBKN4
		---		WBKN5
Product Selection	PRDSL1	PRDSL1	PRDSL1 - dropped	PRDSL1
	PRDSL2	PRDSL2	PRDSL2	PRDSL2

	PRDSL3 - dropped	PRDSL3 - dropped	PRDSL3	PRDSL3
Website Usability	DEGN1 - dropped	DEGN1	DEGN1 - dropped	DEGN1
	DEGN2	DEGN2	DEGN2	DEGN2
	DEGN3	DEGN3 - dropped	DEGN3	DEGN3
	---	---	---	DEGN4
Quality of Detailed Product Information	PRDINF1	PRDINF1	PRDINF1	PRDINF1
	PRDINF2	PRDINF2 - dropped	PRDINF2	PRDINF2
	PRDINF3 - dropped	PRDINF3	PRDINF3	PRDINF3
Purchase Efficiency	PURCH1	PURCH1	PURCH1	PURCH1
	PURCH2 - dropped	PURCH2 - dropped	PURCH2 - dropped	PURCH2
	PURCH3	PURCH3	PURCH3	PURCH3
Delivery Efficiency	DELIV1 - dropped	DELIV1 - dropped	DELIV1 - dropped	DELIV1
	DELIV2	DELIV2	DELIV2	DELIV2
	DELIV3	DELIV3	DELIV3	DELIV3
Post-sales Efficiency	RETRN1	RETRN1	RETRN1 - dropped	RETRN1
	RETRN2	RETRN2	RETRN2	RETRN2
	RETRN3 - dropped	RETRN3	RETRN3	RETRN3
Price Perception	---	---	---	PRICE1
	---	---	---	PRICE2
	---	---	---	PRICE3
Previous Experience	---	Number of orders placed in the past six months	---	Whether shopped at Amazon.com or not

--- Not measured

Appendix 2. Correlations and Descriptive Statistics of the 1st Round Pilot Sample (N=51)

Construct	Mean (Std)	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Quality of PPRs	5.06 (1.41)	1.00												
2. Website Knowledge[a]	1.14 (1.82)	.14	1.00											
3. Product Knowledge[b]	11.06 (6.18)	.07	.04	1.00										
4. Website Usability	5.92 (1.08)	.38 **	.21	-.07	1.00									
5. Product Selection	5.85 (1.13)	.30 *	.04	-.02	.27	1.00								
6. Product Information Quality	5.73 (.88)	.47 **	.18	.28 *	.46 **	.48 **	1.00							
7. Ease of Decision Making	4.98 (1.54)	.35 *	.21	.25	.40 **	.19	.28 *	1.00						
8. Decision Making Confidence	5.44 (1.19)	.06	.03	.10	.07	-.08	.22	.33 *	1.00					
9. Purchase Efficiency	5.15 (1.44)	.05	.41**	-.25	.27	.11	.05	.04	-.04	1.00				
10. Delivery Efficiency	5.98 (1.14)	.15	.11	-.10	.25	.54**	.29*	.26	.12	.21	1.00			
11. Post-sales Efficiency	3.48 (1.67)	.28*	.35*	-.01	.30*	.20	.26	.17	.05	.35 *	.39 **	1.00		
12. Previous Experience	4.45 (1.19)	.01	.30*	.18	.26	.20	.22	.25	-.03	.38 **	.31 *	.36 *	1.00	
13. Repurchase Intention	4.31 (1.36)	.12	.17	.15	.31*	.38**	.28*	.37 **	.000	.16	.44 **	.26	.72 **	1.00

[a] Measured using the number of orders placed with Amazon.com [b] Measured using the number of items watched out of the top seller list

* significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 3. Factor Analysis of the 1st Round Pilot Sample (Part 1) (N=51) (Product Brokering Efficiency Model)

Construct	PPR	DMES	DMCNF	DEGN	PRDINF	PRDSL
PPR1	**[.90]**	.22	.34	.19	.11	.16
PPR2	**[.92]**	.10	.01	.11	.19	.22
PPR3	**[.93]**	.14	.05	.06	.13	-.05
DMES1	.17	**[.90]**	.07	.01	.11	-.03
DMES2	.13	**[.84]**	.28	.15	.04	.20
DMES3	.17	**[.84]**	.19	.26	-.13	.14
DMCNF1	.09	.15	**[.88]**	-.01	.21	-.04
DMCNF2	.02	.15	**[.88]**	-.02	.15	.04
DMCNF3	.05	-.03	**[.88]**	.01	-.05	-.10
DMCNF4	-.08	.25	**[.78]**	.07	-.20	-.10
DEGN1	.01	-.26	.07	**[.63]**	-.05	.57
DEGN2	.21	.15	-.03	**[.85]**	.14	.18
DEGN3	.13	.32	.02	**[.88]**	.11	.03
PRDINF1	.33	.02	.30	.27	**[.73]**	.19
PRDINF2	.09	.26	.09	.33	**[.73]**	.26
PRDINF3	.17	-.14	-.11	-.12	**[.71]**	.21
PRDSL1	.02	.16	-.05	.03	.33	**[.78]**
PRDSL2	.09	.05	-.05	.10	.22	**[.92]**
PRDSL3	.24	.14	-.14	.20	.07	**[.81]**
Total Variance Explained	82%					

PPR – Quality of PPRs; DMES – Ease of Decision Making; DMCNF – Decision Making Confidence; DEGN – Website Usability; PRDINF – Quality of Detailed Product Information; PRDSL – Product Selection

Appendix 4. Factor Analysis of the 1st Round Pilot Sample (Part 2) (N=51) (Repurchase Intention Model)

Construct	DMES	DMCNF	PURCH	DELIV	RETRN	REPUR
DMES1	**[.91]**	.11	.00	-.11	-.04	.13
DMES2	**[.85]**	.26	-.00	.32	.14	.08
DMES3	**[.89]**	.17	.04	.14	.10	.13
DMCNF1	.14	**[.89]**	.13	.11	-.06	-.03
DMCNF2	.14	**[.88]**	.10	.20	-.10	.01
DMCNF3	.00	**[.88]**	-.16	-.05	.05	-.06
DMCNF4	.25	**[.77]**	-.03	-.08	.11	-.10
PURCH1	.13	-.02	**[.81]**	.28	.22	.01
PURCH2	.01	.20	**[.56]**	-.02	.02	.27
PURCH3	-.08	-.14	**[.88]**	-.06	.06	-.13
DELIV1	.10	-.04	-.10	**[.68]**	.18	.47
DELIV2	.01	.13	.09	**[.90]**	.10	.11
DELIV3	.15	.03	.09	**[.80]**	.34	.05
RETRN1	.07	.01	.28	.18	**[.85]**	.10
RETRN2	.05	.05	.19	.16	**[.91]**	.10
RETRN3	.06	-.04	-.14	.16	**[.85]**	.18
REPUR1	.16	.01	.15	.49	.00	**[.73]**
REPUR2	.29	.11	.14	.44	.05	**[.67]**
REPUR3	.18	-.17	-.04	.16	.10	**[.66]**
REPUR4	-.11	-.10	.01	-.23	.35	**[.75]**
Total Variance Explained	77%					

DMES – Ease of Decision Making; DMCNF – Decision Making Confidence; PURCH – Purchase Efficiency; DELIV – Delivery Efficiency; RETRN – Post-sales Efficiency; REPUR – Repurchase Intention

Appendix 5. Reliability of Measurement Scales

Construct	1st Round Pilot (N=51)	2nd Round Pilot (N=40)	Pooled Sample (N=91)	3rd Round Pilot (N=56)
	Cronbach Alpla (number of items)	Cronbach Alpha (number of items)	Cronbach Alpha (number of items)	Cronbach Alpha (number of items)
Quality of PPRs	.97 (2)	.90 (3)	.93 (3)	.93 (6)
Website Knowledge	---	.91 (2)	---	.89 (5)
Product Category Knowledge	---	.77 (3)	---	.83 (3)
Website Usability	.90 (2)	.92 (2)	.83 (2)	.89 (4)
Product Information Quality	.85 (2)	.76 (2)	---	.74 (3)
Product Selection	.88 (2)	.88 (2)	.85 (2)	.81 (3)
Ease of Decision Making	.91 (3)	.93 (3)	.92 (3)	.95 (3)
Ease of Information Search	---	---	---	---
Decision Making Confidence	.88 (4)	.95 (2)	.92 (2)	.92 (5)
Decision Making Satisfaction	---	---	---	.92 (3)
Purchase Efficiency	.78 (2)	.74 (2)	.69 (2)	.74 (3)
Delivery Efficiency	.88 (2)	.63 (2)	.63 (2)	.73 (3)
Post-sales Efficiency	.93 (2)	.86 (3)	.83 (2)	.84 (3)
Repurchase Intention	.80 (3)	.92 (2)	.80 (2)	.78 (3)
Price Perception	---	---	.57 (2)	.86 (3)

Appendix 6. ANOVA Results (Dependent Variable – Quality of PPRs)

Sample (Sample Size)	Number of Subjects	Number of Items Rated	Mean (Std)	F Statistics
1st Round Pilot (N=51)	13	0	4.57(1.41)	1.21
	15	5	4.97 (1.17)	
	12	15	5.21 (1.76)	
	11	30	5.64 (1.21)	
2nd Round Pilot (N=40)	12	0	3.84 (1.81)	3.01 *
	12	5	4.83 (.93)	
	13	15	5.26 (.82)	
	3	30	4.11 (2.17)	
Pooled Sample (N=91)	25	0	4.27 (1.59)	2.75 *
	27	5	4.90 (1.04)	
	25	15	5.22 (1.27)	
	14	30	5.28 (1.43)	
3rd Round Pilot (N=56)	28	5	3.95 (1.53)	4.62 *
	28	15	4.75 (1.21)	

* significant at $\alpha = 0.05$ ** significant at $\alpha = 0.01$ *** significant at $\alpha = 0.001$

Appendix 7. OLS Regression Results of the 1st Round Pilot

Variable	DV – Ease of Decision Making			DV – Decision Making Confidence			DV – Repurchase Intention
	Whole Sample (N=51)	Low Prod Know (N=26)	High Prod Know (N=25)	Whole Sample (N=51)	Low Prod Know (N=26)	High Prod Know (N=25)	Whole Sample (N=51)
	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)
Quality of PPRs	.21 (.17)	.72 (.25) *	-.044 (.21)	.01 (.14)	-.02 (.23)	.26 (.21)	---
Product Knowledge[a]	.07 (.04)	-.39 (.14) *	.08 (.04) *	.02 (.03)	-.15 (.13)	.02 (.04)	---
Website Knowledge[b]	.18 (.25)	.13 (.34)	.22 (.27)	.11 (.21)	-.31 (.31)	.32 (.27)	---
Website Usability	.54 (.23) *	.19 (.32)	.66 (.26) *	-.12 (.19)	.06 (.28)	-.48 (.27)	---
Product Info Quality	-.24 (.33)	-.76 (.38)	.34 (.41)	.58 (.27)	.30 (.35)	.75 (.41)	---
Product Selection	.12 (.21)	.10 (.28)	.21 (.28)	-.26 (.17)	-.23 (.25)	.08 (.29)	---
Ease of Decision Making	---	---	---	---	---	---	.28 (.12)*
Decision Making Quality	---	---	---	---	---	---	-.17 (.15)
Purchase Efficiency	---	---	---	---	---	---	.05 (.13)
Delivery Efficiency	---	---	---	---	---	---	.41 (.17)*
Post-sales Efficiency	---	---	---	---	---	---	.05 (.12)
Constant	.27(1.51)	5.96 (2.14)	-2.99 (1.94)	4.11 (1.26)	6.01 (1.94)	1.57 (1.99)	.94 (1.27)
R-square	28.1%	51.3%	57.9%	14.4%	23.2%	37.7 %	29.2%

[a] Measured using the number of items watched out of the top seller list [b] Measured using the number of orders placed with Amazon.com
* significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 8. Correlations and Descriptive Statistics of the 2nd Round Pilot Sample (N=40)

Construct	Mean (Std)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Quality of PPRs	4.58 (1.38)	1.00													
2. Website Knowledge	4.09 (1.69)	.00	1.00												
3. Product Knowledge (objective)[a]	10.30 (9.02)	-.15	.02	1.00											
4. Product Knowledge (subjective)[b]	4.32 (1.28)	-.19	.09	.15	1.00										
5. Website Usability	5.87 (1.38)	.24	.02	.05	.34*	1.00									
6. Product Selection	5.38 (1.24)	.24	.29	-.11	.03	.28	1.00								
7. Product Information Quality	4.37 (1.37)	-.17	-.01	.14	.95*	.49*	.08	1.00							
8. Ease of Decision Making	4.91 (1.61)	.37*	-.15	.13	.29	.43*	-.03	.38*	1.00						
9. Decision Making Confidence	5.71 (1.09)	.29	-.03	.21	.33*	.46*	.25	.44*	.59*	1.00					
10. Purchase Efficiency	4.94 (1.47)	.32*	.34*	.06	.11	.06	.25	.10	.23	.26	1.00				
11. Delivery Efficiency	5.99 (.92)	.18	.27	-.16	.25	.54*	.29	.28	.39*	.29	.01	1.00			
12. Post-sales Efficiency	3.39 (1.57)	-.04	.30	-.06	.04	-.12	.10	.00	.18	.02	.17	.12	1.00		
13. Previous Experience	.14 (.41)	-.06	.33*	-.14	.20	.10	.00	.18	.04	.18	-.03	.14	.12	1.00	
14. Repurchase Intention	4.23 (1.39)	.24	.33*	-.03	.09	.28*	.06	.09	.22	-.04	-.01	.39*	.21	.21	1.00

[a] Measured using the number of items watched out of the top seller list [b] Measured using consumers' subjective evaluation
* significant at $\alpha = 0.05$

Appendix 9. Factor Analysis of the 2ⁿᵈ Round Pilot Sample (Part 1) (N=40) (Product Brokering Efficiency Model)

Construct	PPR	WBKN	PRDKN	DMES	DMCNF	DEGN	PRDINF	PRDSL
PPR1	**[.93]**	-.01	.06	.00	.03	.04	-.14	.11
PPR2	**[.92]**	.04	-.08	-.12	-.04	-.04	.07	-.08
PPR3	**[.89]**	-.04	-.01	.05	-.01	-.01	.16	.12
WBKN2	-.02	**[.92]**	.02	.01	-.09	.09	.08	.18
WBKN3	.01	**[.92]**	.00	-.18	-.01	.09	.02	.04
PRDKN1	.18	-.07	**[.73]**	.06	-.08	.38	.11	.15
PRDKN2	-.06	.25	**[.87]**	-.05	-.04	-.12	-.01	-.03
PRDKN3	-.09	.04	**[.83]**	.00	.26	.09	.01	-.06
DMES1	-.03	-.09	.05	**[.89]**	.20	.16	.09	.06
DMES2	.02	-.07	-.07	**[.90]**	.16	.17	.17	-.10
DMES3	-.06	-.11	.01	**[.92]**	.08	.05	.05	-.01
DMCNF1	-.07	.02	.01	.26	**[.89]**	.22	.15	.09
DMCNF2	.06	-.06	.15	.21	**[.87]**	.12	.27	.14
DEGN1	.07	-.02	.06	.11	.24	**[.92]**	.16	.06
DEGN2	.00	.04	.14	.29	.11	**[.85]**	.22	.13
PRDINF1	.09	-.03	.13	.15	.12	.29	**[.80]**	.23
PRDINF3	.02	.15	-.04	.17	.30	.13	**[.83]**	.07
PRDSL1	.01	.17	-.02	-.04	.06	.28	.06	**[.90]**
PRDSL2	.14	.16	.04	-.02	.15	-.07	.19	**[.91]**
Total Variance Explained	88.02%							

WBKN – Website Knowledge; PRDKN – Product Category Knowledge; PPR – Quality of PPRs; DMES – Ease of Decision Making; DMCNF – Decision Making Confidence; DEGN – Website Usability; PRDINF - Quality of Detailed Product Information; PRDSL – Product Selection

Appendix 10. Factor Analysis of the 2nd Round Pilot Sample (Part 2) (N=40) (Repurchase Intention Model)

Construct	DMES	DMCNF	PURCH	DELIV	RETRN	REPUR
DMES1	**[.90]**	.21	.09	.09	.08	.04
DMES2	**[.88]**	.24	.00	.06	.11	.09
DMES3	**[.92]**	.09	.04	.00	.04	.07
DMCNF1	.28	**[.93]**	.04	.11	.02	.00
DMCNF2	.24	**[.90]**	.15	.22	.02	-.09
PURCH1	.26	-.03	**[.85]**	-.17	.23	-.01
PURCH3	-.11	.22	**[.88]**	.22	.07	-.03
DELIV2	-.08	.23	.14	**[.84]**	.16	.04
DELIV3	.25	.08	-.11	**[.82]**	-.02	.26
RETRN1	.06	.01	.35	-.02	**[.84]**	-.09
RETRN2	-.03	.09	-.06	.06	**[.95]**	.14
RETRN3	.19	-.04	.09	.11	**[.82]**	.12
REPUR1	.12	-.09	-.07	.17	.20	**[.91]**
REPUR2	.06	.00	.02	.08	-.00	**[.97]**
Total Variance Explained	87.64%					

DMES – Ease of Decision Making; DMCNF – Decision Making Confidence; PURCH – Purchase Efficiency; DELIV – Delivery Efficiency; RETRN – Post-sales Efficiency; REPUR – Repurchase Intention

Appendix 11. OLS Regression Results of the 2nd Round Pilot (N=40)

Variable	DV – Ease of Decision Making		DV – Decision Making Confidence		DV – Repurchase Intention	
	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)
Quality of PPRs	.27 (.17)	.31 (.17) [†]	.10 (.13)	.15 (.13)	---	---
Product Knowledge (subjective)[a]	.27 (.18)	---	.22 (.14)	---	---	---
Product Knowledge (objective)[b]	---	.02 (.02)	---	.02 (.02)	---	---
Website Knowledge[c]	-.11 (.13)	-.09 (.13)	-.06 (.09)	-.05 (.09)	---	---
Website Usability	.35 (.17)	.26 (.19)	.23 (.13) [†]	.15 (.13)	---	---
Product Information Quality	---	.32 (.19)	---	.26 (.14) [†]	---	---
Product Selection	-.18 (.18)	-.17 (.19)	.14 (.14)	.16 (.14)	---	---
Ease of Decision Making	---	---	---	---	.28 (.12) *	.23 (.19)
Decision Making Confidence	---	---	---	---	-.30 (.18)	-.41 (.25)
Purchase Efficiency	---	---	---	---	.01 (.13)	-.02 (.15)
Delivery Efficiency	---	---	---	---	.72 (.21) **	.53 (.25) *
Post-sales Efficiency	---	---	---	---	.18 (.12)	.10 (.15)
Previous Experience	---	---	---	---	---	.54 (.51)
Constant	1.96 (1.39)	1.75 (1.38)	2.38 (1.03)	2.01 (.99)	-.24 (1.39)	1.93 (1.71)
R-square	30%	32.5%	29.2%	36.1%	41.2 %	25.4%

[a] Measured using consumers' subjective evaluation   [b] Measured using the number of items watched out of the top seller list
[c] Measured using consumers' subjective evaluation
[†] significant at α = 0.1   * significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 12. Correlations and Descriptive Statistics of the Pooled Sample (N=91)

Construct	Mean (Std)	1	2	3	4	5	6	7	8	9	10	11
1. Quality of PPRs	4.85 (1.38)	1.00										
2. Website Knowledge[a]	1.07 (.77)	.02	1.00									
3. Product Knowledge[b]	10.57 (7.53)	-.01	-.05	1.00								
4. Website Usability	5.75 (1.04)	.25*	.09	.08	1.00							
5. Product Selection	5.59 (1.27)	.35*	.00	-.02	.35*	1.00						
6. Ease of Decision Making	5.02 (1.54)	.29*	.01	.21	.43*	.07	1.00					
7. Decision Making Confidence	5.75 (1.14)	.13	.10	.09	.35*	.07	.37*	1.00				
8. Purchase Efficiency	5.23 (1.36)	.02	.39*	-.08	.35*	.26*	.03	.10	1.00			
9. Delivery Efficiency	5.86 (.97)	.18	.16	.11	.31*	.33*	.28*	.34*	.18	1.00		
10. Post-sales Efficiency	3.48 (1.59)	-.00	.23*	.01	.15	.18	.18	.03	.31*	.28*	1.00	
11. Repurchase Intention	4.48 (1.50)	.20	.02	.00	.32*	.40*	.30*	.07	.21*	.35*	.39*	1.00
12. Price Tolerance	3.27 (1.36)	-.09	.25*	.13	.08	.18	.05	-.12	.09	.00	.19	.27*

[a] Measured using the number of orders placed with Amazon.com   [b] Measured using the number of items watched out of the top seller list
* significant at $\alpha = 0.05$

Appendix 13. Factor Analysis of the Pooled Sample (N=91)

Construct	PPR	DEGN	PRDSL	DMES	DMCNF	PURCH	DELIV	RETRN	REPUR	PRICE
PPR1	**[.92]**	.08	.14	.14	.05	-.07	.09	-.07	.01	.02
PPR2	**[.93]**	.03	.11	.04	-.00	.05	.14	.07	.06	-.01
PPR3	**[.88]**	.08	.12	.19	.09	-.01	-.10	-.03	.07	-.13
DEGN2	.17	**[.82]**	.14	.14	.16	.19	.17	-.07	.16	.04
DEGN3	.08	**[.78]**	.15	.31	.17	.19	.01	.13	.04	.04
PRDSL2	.12	.15	**[.87]**	-.04	.02	.11	.14	-.02	.17	.08
PRDSL3	.28	.10	**[.85]**	.05	-.10	.05	.04	.18	.15	.08
DMES1	.12	.18	.03	**[.87]**	.12	-.11	.10	.03	.13	.02
DMES2	.17	.11	-.04	**[.85]**	.24	.01	.24	.09	.11	.03
DMES3	.11	.09	.02	**[.91]**	.19	.04	-.07	.08	.04	.04
DMCNF1	.02	.07	-.06	.16	**[.90]**	.08	.14	.02	-.06	-.02
DMCNF2	.02	.09	.03	.20	**[.88]**	.00	.23	-.03	.02	-.12
DMCNF3	.08	.11	-.02	.14	**[.82]**	-.10	-.13	.05	.09	.04
PURCH1	.04	.12	.09	-.00	.04	**[.81]**	.06	.24	.17	.07
PURCH3	-.06	.15	.06	-.04	-.05	**[.87]**	.01	.04	-.03	-.02
DELIV2	.08	.03	.06	.16	.06	-.10	**[.80]**	.11	.31	-.17
DELIV3	.06	.12	.13	.05	.15	.17	**[.83]**	.14	-.03	.15
RETRN2	-.01	.07	.10	.12	.06	.21	.12	**[.89]**	-.01	-.01
RETRN3	.02	-.02	.02	.04	-.02	.07	.12	**[.86]**	.31	.12
REPUR1	-.01	.10	.22	.16	-.01	.01	.10	.26	**[.85]**	-.03
REPUR2	.21	.11	.15	.13	.07	.15	.15	.04	**[.79]**	.31
REPUR3	.02	-.13	.17	.12	.04	.13	.02	-.02	.12	**[.87]**
REPUR4	-.17	.30	-.03	-.05	-.18	-.13	-.03	.21	.06	**[.73]**
Total Variance Explained	85.36%									

PPR – Quality of PPRs; DMES – Ease of Decision Making; DMCNF – Decision Making Confidence; DEGN –
Website Usability; PRDINF - Quality of Detailed Product Information; PRDSL – Product Selection; PURCH –
Purchase Efficiency; DELIV – Delivery Efficiency; RETRN – Post-sales Efficiency; PRICE – Price Perception;
REPUR – Repurchase Intention

Appendix 14. OLS Regression Results of the Pooled Sample

Variable	DV – Ease of Decision Making			DV – Decision Making Confidence			DV – Repurchase Intention
	Whole Sample (N=91)	Low Prod Knowledge (N=46)	High Prod Knowledge (N=45)	Whole Sample (N=91)	Low Prod Knowledge (N=46)	High Prod Knowledge (N=45)	Whole Sample (N=91)
	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)	B (Std Error)
Quality of PPRs	.26 (.11) *	.42 (.19) *	.06 (.13)	.04 (.08)	.01 (.14)	.14 (.12)	---
Product Knowledge[a]	.03 (.02)	-.08 (.11)	.03 (.03)	.01 (.02)	-.03 (.07)	.01 (.02)	---
Website Knowledge[b]	-.01 (.18)	-.08 (.29)	.02 (.23)	.11 (.14)	-.21 (.20)	.43 (.22) [†]	---
Website Usability	.69 (.15) ***	.48 (.24) *	1.17 (.21) ***	.53 (.12) ***	.69 (.16) ***	.34 (.19) [†]	---
Product Selection	-.25 (.13) [†]	-.22 (.18)	-.33 (.19)	-.14 (.09)	-.19 (.12)	-.06 (.18)	---
Ease of Decision Making	---	---	---	---	---	---	.22 (.10) *
Decision Making Confidence	---	---	---	---	---	---	-.14 (.14)
Purchase Efficiency	---	---	---	---	---	---	.11 (.11)
Delivery Efficiency	---	---	---	---	---	---	.36 (.16) *
Post-sales Efficiency	---	---	---	---	---	---	.24 (.10) *
Constant	.87 (.91)	1.82 (1.40)	-.53 (1.35)	3.14 (.71)	3.19 (.96)	2.91 (1.28)	.73 (1.05)
R-square	29.7%	17.1%	52.1 %	21.5 %	32.8%	21.0%	25.9%

[a] Measured using the number of items watched out of the top seller list [b] Measured using the number of orders placed with Amazon.com
[†] significant at α = 0.1   * significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 15. Correlations and Descriptive Statistics of the 3rd Round Pilot Sample (N=56)

Construct	Mean (Std)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Quality of PPRs	4.58 (1.24)	1.00																		
2. Website Knowledge	4.21 (1.28)	-.15	1.00																	
3. Product Knowledge[a]	29.78 (13.62)	.25	.00	1.00																
4. Product Knowledge[b]	5.16 (1.38)	.29*	.06	.57*	1.00															
5. Website Usability	5.17 (1.08)	.21	.11	.08	.25	1.00														
6. Product Selection	5.09 (1.14)	.13	.16	.31*	.03	.26*	1.00													
7. Product Info Quality	5.33 (1.04)	.02	.18	.10	.13	.37*	.32*	1.00												
8. Ease of DM[c]	3.80 (1.67)	-.39*	.07	.14	.07	.21	.04	.01	1.00											
9. DM[c] Time	455.02 (270.10)	.05	.09	-.27*	-.32*	-.29*	.06	-.08	.10	1.00										
10. DM[c] Confidence	5.53 (.95)	.22	.17	.19	.17	.33*	.24	.30*	.17	-.15	1.00									
11. DM[c] Satisfaction	4.26 (1.23)	.36*	.32*	.24	.22	.45*	.20	.28*	.01	-.13	.45*	1.00								
12. Purchase Efficiency	4.08 (1.83)	-.06	.22	.05	.09	.29*	.22	.26*	.01	-.08	.32*	.28*	1.00							
13. Delivery Efficiency	4.99 (1.28)	.12	.33*	.18	.08	.27*	.35*	.33*	.02	-.21	.31*	.34*	.43*	1.00						
14. Post-sales Efficiency	4.00 (1.34)	.06	.09	.08	.09	.13	.16	.02	.15	.11	.13	-.05	.05	.09	1.00					
15. Price Perception	4.98 (1.41)	.17	.06	.26*	.25*	.15	.12	.19	.10	-.20	.02	.26*	.25	.32*	.09	1.00				
16. Gender	.44 (.50)	.03	-.11	.13	.13	.08	.26*	.10	.25	.01	.18	.05	.14	.01	.04	-.03	1.00			
17. Age	20.05 (1.20)	.01	.08	.28*	.10	.07	.06	.10	.08	.27*	-.07	-.12	-.27*	-.12	.00	-.04	-.09	1.00		
18. Internet Experience	7.66 (2.11)	.09	.19	.15	.07	.14	.01	.14	.01	.00	.21	.03	.19	.19	-.09	-.02	.01	.17	1.00	
19. Previous Experience	.61 (.49)	.02	.34*	.15	.21	.12	.02	-.13	.31*	.08	-.05	-.04	.23	.31*	.00	-.10	-.15	-.03	-.23	1.00
20. Repurchase Intention	4.14 (1.18)	.24	.25*	.17	.07	.09	.07	.32*	.22	-.01	.09	.49*	.36*	.09	-.06	.39*	.02	.14	.09	.19

[a] Measured using the number of items watched out of the top seller list [b] Measured using consumers' subjective evaluation [c] Decision Making

* significant at α = 0.05

Appendix 16. OLS Regression Results of the 3rd Round Pilot (N=56)

Appendix 16. OLS Regression Results of the 3rd Round Pilot (N=56)

Variable	Product Brokering Costs		Product Brokering Quality		Store Loyalty
	DM[a] Time B (Std Error)	Ease of DM[a] B (Std Error)	DM[a] Satisfaction B (Std Error)	DM[a] Confidence B (Std Error)	Repurchase Intention B (Std Error)
Quality of PPRs	17.26 (.26.81)	.41 (.18) *	.29 (.11) *	.12 (.10)	---
Product Knowledge	-83.53 (25.99) **	.03 (.16)	-.11 (.10)	.05 (.09)	---
Website Knowledge	22.43 (26.04)	.16 (.16)	.29 (.11) **	.10 (.09)	---
PPR X Product Knowledge	-55.31 (21.10) *	.29 (.14) †	-.19 (.09) †	-.01 (.08)	---
Website Usability	74.96 (.35.46) *	-.37 (.21) †	.48 (.13) **	.20 (.12)	---
Product Information Quality	-58.85 (.39.07)	.02 (.23)	.18 (.15)	.12 (.14)	---
Product Selection	11.89 (32.24)	.05 (.20)	-.09 (.13)	.13 (.12)	---
DM[a] Time	---	---	---	---	-.00 (.00)
DM[a] Satisfaction	---	---	---	---	.48 (.10) ***
Purchase Efficiency	---	---	---	---	.41 (.15) *
Delivery Efficiency	---	---	---	---	-.13 (.18)
Post-sales Efficiency	---	---	---	---	-.02 (.09)
Price Perception	---	---	---	---	.28 (.08) **
Gender	53.36 (68.33)	1.32 (.44) *	.03 (.27)	.39 (.25)	.01 (.23)
Age	107.08 (26.18) ***	-.02 (.16)	-4.60 (.11)	-.07 (.09)	.08 (.11)
Internet Experience	-5.86 (15.27)	-.05 (.09)	-.11 (.06)	.06 (.06)	.06 (.06)
Previous Experience	---	---	---	---	-.40 (.25)
Constant	-1569.74 (564.07)	3.23 (3.53)	1.19 (2.31)	2.54 (2.13)	2.25 (2.49)
R-square	41.3%	37.1%	48.9%	32.2%	50.8%

[a] DM – Decision Making

† significant at α = 0.1   * significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 17. Power Analysis of the 3rd Round Pilot (N=56)

	DM[a] Time	DM[a] Difficulty	DM[a] Satisfaction	DM[a] Confidence	Repurchase Intention
Quality of PPR	1169	**104**	**74**	352	---
Website Knowledge	702	502	**63**	479	---
Product Knowledge	**48**	∞	422	1753	---
PPR X Product Knowledge	**72**	**117**	**121**	∞	---
DM[a] Time	---	---	---	---	5257
DM[a] Difficulty	---	---	---	---	803
DM[a] Satisfaction	---	---	---	---	**24**

[a] DM – Decision Making

Numbers in bold indicate the relationship will be significant at $\alpha = 0.05$ with a sample size of 250.

Appendix 18. Discussion of Pretests and Pilot Studies

Summary of the Pretests

Four rounds of pretest were conducted in late March, 2004 among 15 Ph.D. students in the business school to determine if there were any problems with the experimental design. The experiment was conducted in a computer lab. First, the subjects were randomly assigned to one of the four treatment groups. Then, they logged on to Amazon.com as a new customer with fake personal information. Next, they rated a certain number of DVD items they had watched before. Finally, they evaluated the quality of PPRs and completed a purchase task. After each round, the experimental procedure was modified based on the subjects' feedback, then, the revised experiment protocol was used for the next round. Problems that were fixed through the four rounds of pretests include unclear instructions, and irrelevant or confusing questions. In addition, the length of the study was found to be a big concern. On average, it took the subjects 50 minutes to finish the experiment in the pretests. When the experiment is too long, subjects get tired and bored quickly and do not provide reliable responses. Therefore, to ensure that the experiment could be completed within half an hour, I shortened the study by cutting some steps and deleting some measurement items. Items that measure consumers' unfavorable behavioral intentions and the two objective measures of consumer online product brokering costs – the total decision making time and the total number of pages browsed by consumers – were dropped during the pretests.

The 1st Round Pilot Study

The 1st round pilot study was conducted at the end of April, 2004. A total of 51 undergraduate students in the business school were recruited. All the subjects were randomly assigned to the four treatment groups. As it was very hard to schedule a time that was convenient for most of the subjects, especially at the end of a semester, they were allowed to take it home and finish it on their own time.

The pilot study was planned to achieve the following goals: (1) to evaluate the validity and reliability of all the measurement scales; (2) to check if the experimental design has any problems such as if the manipulation is successful or not; and (3) to examine the distributions of all the control variables and consumers' repurchase intention to see how far they deviate from normality.

Results of Statistical Analyses

The correlation matrix and descriptive statistics of all the variables are presented in Appendix 2. To examine the psychometric properties of all measurement scales, a factor analysis with varimax rotation was performed first with SPSS and the final results are presented in Appendix 3 and 4. All the eleven constructs demonstrated satisfactory internal consistency with Cronbach's alpha greater than 0.7 (see Appendix 5). The measurement scales used in this round of pilot are summarized in Appendix 1. The distribution of all the constructs did not show significant deviation from normality except for consumers' website knowledge measured using the total number of orders placed at Amazon.com during the past six months. A square root transformation was performed on this variable to reduce its skewness and the transformed variable was used for further analysis.

A one-way ANOVA was conducted to compare the quality of PPRs perceived by subjects across the four treatment groups as a manipulation check. The results show that the mean of perceived quality of PPRs increased from group 1 to group 4, just as predicted, but the difference was not statistically significant (see Appendix 6).

Because of the small sample size, a series of regression analyses were performed to estimate the research model. To test for the moderating effect of product category knowledge, first, the sample was split into two groups – high vs. low product knowledge – with the median as the cutting point. Then, I conducted a regression analysis with each subsample separately. The results of all the regression analyses are presented in Appendix 7.

The 2nd Round Pilot Study

A second-round pilot study was conducted in late August, 2004 among 43 undergraduate students in the business school to further improve the design of the experiment. Because of missing data, three returned surveys were discarded, resulting in a sample size of 40.

Modifications to the Experimental Design

In this round of pilot, two major changes were made to the experimental procedures. First, all the subjects were asked to evaluate the quality of PPRs after they made their purchase decisions, while in the 1st round pilot study, they did this before the purchase. This change was made because the evaluation process may interfere with

subjects' decision making process and increase their likelihood of utilizing PPRs, and ultimately produce biased results.

Another major change was that in this round of pilot study, the experiment was conducted in two phases. In Phase I, all the subjects were given a list of Amazon.com's 100 top seller DVDs to rate all the items they had watched before. Then, I created a fake account for each subject at Amazon.com and entered the first 5, 10, 15, or 30 product ratings into their account. Two days later, in Phase II, they finished a simulated purchase and filled out the survey in the computer lab. Recall that in the 1st round pilot, the whole study was completed in one time slot and the subjects made the purchase immediately after they provided product ratings. This change was made because in real life, there is normally a time lag between the two activities. Making the simulated purchase setting as close as to what the subjects experience in their daily life will help us better understand how the subjects react to PPRs in real purchase settings. Moreover, by letting the researcher enter the product ratings for all the subjects behind the scene, the two-phase design also helps shorten the length of the experiment.

In addition, in this round of pilot study, changes were also made to the measurement of some constructs. First, subjective measures of consumers' product category knowledge and website knowledge were collected. At the same time, the total number of orders placed with Amazon.com during the past six months was used to measure consumers' previous experience with the online store rather than consumers' website knowledge as in the 1st round pilot study. Because consumers can also accumulate their website knowledge from visits that do not result in any purchases, the total number of orders is not an accurate measure of consumers' website knowledge.

Alternatively, consumers' website knowledge can be objectively evaluated with the total number of visits to Amazon.com or the frequency of visits to Amazon.com during a certain period of time, however, results of the 1st round pilot study show that subjects had difficulty providing such estimates. Therefore, in this round of pilot study, consumers' website knowledge was only measured subjectively with their self-reported familiarity with Amazon.com's website interface and frequency of visits to Amazon.com.

Results of Statistical Analyses

The correlation matrix and descriptive statistics of all the variables are presented in Appendix 8. A factor analysis with varimax rotation was performed using SPSS to evaluate the psychometric properties of all the measurement scales and the final results are shown in Appendix 9 and 10. All the constructs demonstrated satisfactory internal consistency with Cronbach's alpha greater than 0.7 except for delivery efficiency, which had an alpha value of .63 (see Appendix 5). Items used to measure all the constructs in the final analysis are listed in Appendix 1. The average score for each multi-item construct was obtained and the distributions of all the constructs were examined by checking its skewness and kurtosis. No significant departure from normality was found for any of the variables except for previous experience measured using the total number of orders placed with Amazon.com during the past six months. Consistent with what it was found in the first-round of pilot, only five subjects in the sample had ever shopped at Amazon.com.

A one-way ANOVA was conducted to compare the quality of PPRs perceived by subjects across the four treatment groups as a manipulation check. The results show that the quality of PPRs was significantly different across the four groups (see Appendix 6). Consistent with my prediction, when consumers' input to the recommender system increased, the quality of PPRs improved. At the same time, it implies that the relationship between consumers' level of input and the quality of PPRs may not be linear.

As in the first-round pilot study, two sets of regressions were conducted to estimate the product brokering efficiency model and the repurchase intention model separately. To check for the moderating effect of product category knowledge, first, the sample was split into two groups – high vs. low product knowledge – with the median as the cutting point. Because the sample size (only 18 and 22 subjects in each of the two subsamples) was too small for regression analysis, only the bivariate correlations between the quality of PPRs and the two dependent variables – ease of product brokering and product brokering quality – were examined. The correlation was higher for the low knowledge group in both the two cases, but whether the difference is significant or not needs to be formally tested. The results are reported in Appendix 11.

The Pooled Sample

To test the research model with a higher statistical power, the samples of the 1st round and 2nd round pilot studies were pooled together, resulting in a total sample size of 91. It should be noted that the two constructs – consumer product category knowledge and website knowledge – were measured differently in the two round pilot studies. In the 1st round pilot, only objective measures of these two constructs were collected, while in

the 2nd round pilot, subjective measures were added. Because the subjective measures of the two constructs were not available for the first-round sample, only objective measures were used in the analyses using the pooled sample.

Results of Statistical Analyses

The correlation matrix and descriptive statistics of all the variables are presented in Appendix 12. To evaluate the psychometric properties of all the measurement scales, a factor analysis with varimax rotation was performed with all the constructs included and the final results are presented in Appendix 13. All the constructs demonstrated satisfactory internal consistency with Cronbach's alpha greater than 0.7 except for purchase efficiency (.69), delivery efficiency (.63), and price tolerance (.57) (see Appendix 5). The average score for each multi-item construct was obtained and the distributions of all the constructs were examined by checking its skewness and kurtosis. Consistent with the results of the 1st round pilot study, the only variable that had problems was consumers' website knowledge measured using the total number of orders placed at Amazon.com during the past six months. About a third of subjects in the sample had never purchased anything from Amazon.com during the past six months. A square root transformation was performed on this variable to reduce its skewness and the transformed variable was used for further analysis.

A one-way ANOVA was conducted to compare the quality of PPRs perceived by subjects across the four treatment groups as a manipulation check. Consistent with the results of the 2nd round pilot study, the perceived quality of PPRs was significantly different across the four groups (see Appendix 6).

Two separate regressions were conducted to estimate the product brokering efficiency model and the repurchase intention model respectively. To test for the moderating effect of product category knowledge, first, the whole sample was split into two groups – high vs. low product knowledge – with the median as the cutting point. Then, a regression was performed with each subsample separately. The results of all the regression analyses are presented in Appendix 14.

Discussion

Several conclusions can be drawn from the results of the first two rounds of pilot studies. First, the experimental design used in the 2nd round pilot study proved to be feasible. It shortens and simplifies the experimental procedure and at the same time, makes the simulated purchase setting closer to what happens in real life. Second, most measurement scales demonstrated satisfactory psychometric properties. Third, it was encouraging to see that the dependent variable, consumer repurchase intention, and almost all control variables did not show significant deviation from normality. The only concern was consumers' previous experience with Amazon.com, which was measured using the total number of orders placed with Amazon.com during the past six months. Results of the pilot studies show that the majority of undergraduate students have never shopped at Amazon.com and this variable always had a skewed distribution. A better measurement for consumers' previous experience with Amazon.com should be used in the final data collection. Finally, the manipulation of the quality of PPRs was successful. The ANOVA test was significant in the 2nd round pilot and with the pooled sample. Moreover, the distribution of the quality of PPRs was found to be close to normality in

both the two rounds of pilot studies, which indicates that the manipulation generated

sufficient variance for the core variable in the model.

Because of the small sample size, it was too early to draw any conclusions about

hypotheses testing. Here, I just briefly discuss some major issues that need to be further

investigated in the final study.

The product brokering quality model produced very poor results. It was not

significant in the 1st round pilot. Although it became significant in the 2nd round pilot and

with the pooled sample, the quality of PPRs was never significant. Moreover, the

bivariate correlation between the quality of PPRs and product brokering quality

measuring using consumer decision making confidence was very low and not significant.

The existing literature offers two possible explanations. First, although PPRs may save

consumers' cognitive effort at the product screening stage, the freed cognitive resource

may not be used by consumers to better evaluate alternatives at the evaluation stage and

reach a higher quality purchase decision, as predicted in the model (Todd and Benbasat

1992). Second, product brokering quality was operationalized as the extent to which

consumers are confident in the items they have selected. Previous studies (e.g., Alba and

Hutchinson 2000) have found that consumers demonstrate overconfidence in many

decision making situations, and thus, consumers' self-evaluated confidence in their

purchase decisions may not be an accurate measure of their product brokering quality.

Because DVDs belong to the category of subjective products and there is no mechanism

to objectively evaluate consumers' choices, the development of a more accurate measure

of product brokering quality is very challenging, if not completely impossible.

Another surprising finding was that consumer learning (consumer product category knowledge and website knowledge) did not show significant impact on product brokering efficiency. For consumer website knowledge, one possible explanation is that Amazon.com's website is so user-friendly that consumers with low website knowledge can undertake information search just as efficiently as consumers with high website knowledge. The strong impact of website usability on consumer product brokering efficiency, as revealed by the regression analysis, is consistent with this conjecture. This finding implies a dilemma faced by online retailers. Improving the usability of their website will make consumers' online shopping more efficient, which in turn will increase their future repurchase intention. However, at the same time, consumers' accumulated website knowledge will be less important and online retailers will lose an opportunity to lock in their customers by taking advantage of this consumer learning effect.

As to consumer product category knowledge, the insignificant result may be due to the specific product category targeted in this study. Although much empirical evidence has shown that expert consumers enjoy significant advantages over novice consumers in decision making, i.e., experts incur lower cognitive cost and are able to make more informed purchase decisions, all previous studies have examined this phenomenon in the context of complex products such as sewing machines and motorcycles (e.g., Brucks 1985; Mitchell and Dacin 1996). As discussed earlier, the advantages possessed by experts mainly come from stronger analytic skills for information processing and greater amount of product information stored in their memory. Strong analytic skills make consumer product brokering more efficient only when the products are very complex so that analytic skills are necessary for product

evaluation. In the context of simple products such as movie DVDs, stronger analytic skills may not show any significant impact. Greater amount of stored product information should save consumers' time and cognitive effort for product evaluation regardless of the complexity of the products. However, this may not be that simple under some circumstances. On one hand, because real movie titles are used in this study, consumers who have either watched a movie or have heard about a movie from various sources do not need to go through the detailed information to make their judgment, and therefore, should be able to make their purchase decision easily and quickly. On the other hand, consumers who are more knowledgeable about movies may form a larger consideration set, i.e., have more items to choose from, and thus, have more difficulty reaching their purchase decision. Therefore, in the specific context of this study, because product knowledge may influence consumer product brokering efficiency in opposite directions, I may not be able to observe any significant findings.

Finally, the moderating effect of consumer product knowledge still needs to be tested. Although the coefficients of the quality of PPRs obtained from the two separate regression analyses using the high knowledge and low knowledge sub-samples were different, no formal test was conducted due to small sample size.

The 3rd Round Pilot study

In order to further improve the design of the study by incorporating the feedback from the proposal defense, the 3rd round pilot study was conducted in late December 2004. A total of 59 undergraduate students from the business school participated in this study.

Modifications to the Experimental Design

In previous two rounds of pilot studies, when randomly assigning subjects to different treatment conditions, some subjects (two in the first-round and three in the second-round) were assigned to a treatment group in which they were required to rate more items than they actually had watched, and these subjects had to be reassigned to another group. Obviously, this violated the randomization procedure and may bias the results. One solution to this problem is to ask subjects to rate the required number of items even though they may not have watched them. However, subjects cannot provide reliable ratings for items they have not watched. Another solution is to screen all the subjects first and drop those who have not watched the minimal number of items, then randomly assign the subjects to different treatment conditions.

Two important issues need to be considered when setting the threshold. First, it should not be too high to avoid losing many subjects. In addition, it should not be too low to ensure that sufficient variance can be generated for the core variable – perceived quality of PPRs. Previous pilot studies show that the perceived quality of PPRs was significantly different between the 15-item and 5-item groups, but no significant difference was found between 5-item and 10-item groups, as well as between 15-item and 30-item groups, therefore, I decided to limit the treatment conditions to only two levels – high input (15 items) and low input (5 items) and set the threshold to 15 items.

In this round of pilot study, after the subjects' product ratings were collected in Phase I, a screening was conducted first to drop those subjects who had watched fewer

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than 15 items, then, the rest of the subjects were randomly assigned to one of the two treatment conditions.

Other changes made in this round of pilot include: First, the total amount of time expended on decision making was collected as an objective measure of consumer decision making cost and consumers' satisfaction with the decision making process was evaluated as an alternative measure of consumer decision making quality. Therefore, in this round of pilot, online product brokering cost was measured subjectively using consumers' self-reported decision making difficulty as well as objectively using the total amount of time expended on decision making. Online product brokering quality was evaluated using both consumers' self-reported confidence in their purchase decisions and satisfaction with the decision making process. Second, in order to keep track of the total amount of time the subjects expended on decision making, Media Lab – a software package for designing and running behavioral experiments – was used for data collection in this round of pilot. An important feature of Media Lab is that it can automatically collect the subjects' clickstream data when they are browsing at Amazon.com. Finally, individual consumer characteristics including their age, gender, Internet experience, and online shopping experience were collected and used as control variables in the model.

Results of Statistical Analyses

The correlation matrix and descriptive statistics of all the variables are presented in Appendix 15. To evaluate the psychometric properties of all the multi-item constructs, first, pairwise factor analysis with varimax rotation was performed using SPSS and items that were dropped during the process are listed in Appendix 1. All the constructs demonstrated satisfactory internal consistency with Cronbach's alpha greater than 0.7

(see Appendix 5). The distribution of all the constructs was reasonably close to normality except for consumer decision making confidence with most responses centering on a high value.

One-way ANOVA was conducted to compare the quality of PPRs perceived by subjects between the two treatment groups. Consistent with my prediction, the results show that subjects in the 15-item group perceived the quality of PPRs significantly higher than subjects in the 5-item group (see Appendix 6).

Results of all the regression analyses are presented in Appendix 16. It should be noted that a different method was used to test for the interaction effect of the quality of PPRs and consumer product category knowledge. Because the sample size would be too small to produce any meaningful results if splitting the sample into two groups, an interaction term was created and entered into the regression model. To reduce multicollinearity, the two variables were centered first before they were multiplied together.

Power Analysis

Power analysis was performed for all the core variables to estimate the minimal sample size required for the final data collection. Assuming that sample characteristics are the same, the results of the power analysis indicate that with 90% chance, the following variables would be significant with a sample size of 250 (see Appendix 17): (1) decision making time as dependent variable – product knowledge and the interaction of the quality of PPRs and product knowledge; (2) decision making difficulty as dependent variable – quality of PPRs and the interaction of PPRs and product knowledge; (3)

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decision making satisfaction as dependent variable – product recommendations, website knowledge, and the interaction of PPRs and product knowledge; (4) decision making confidence as dependent variable – none; and (5) repurchase intention as dependent variable – decision making satisfaction.

Therefore, with a sample size of 250 and 90% chance, the results of hypotheses testing would be as follows: (1) the impact of PPRs on consumer product brokering cost would be mixed (H1a). Higher quality PPRs actually can increase consumer decision making difficulty and either increase or reduce consumer total decision making time depending on the level of product knowledge possessed by individual consumers. (2) Higher quality PPRs can significantly improve consumer product brokering quality by increasing their decision making satisfaction (H1b). (3) Higher level product knowledge can significantly reduce consumer product brokering cost by reducing their total decision making time (H2a). (4) Higher level website knowledge can significantly improve consumer product brokering quality by increasing their decision making satisfaction (H3b). (5) The impact of the quality of PPRs on consumer product brokering cost – total decision making time and decision making difficulty (H4a) and product brokering quality – decision making satisfaction (H4b) would be moderated by consumer product knowledge; and finally, (6) consumers who experience a higher product brokering quality – higher decision making satisfaction (H5b) would have a higher repurchase intention.

In summery, the results of power analysis indicate that a sample of 250 subjects should have sufficient power to detect most of the hypothesized effects. In addition, due to the complexity of the experimental design, the sample size cannot be too large and 250 is a manageable size.

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<u>Discussion</u>

Because of the small sample size, the results obtained from the regression analyses are preliminary and no conclusions can be drawn at this stage. The following are discussions about some issues that need to be further investigated in the final study.

In this round of pilot study, consumer product brokering cost was measured in two ways – consumer decision making time and perceived decision making difficulty. It is interesting to find that the correlation between the two measures was very low and not significant. The results of regression analyses using these two variables as dependent variables were also very different. There are two possible explanations. First, as concluded by many previous studies in the consumer behavior literature, consumers' subjective evaluation is usually not very accurate. However, it is also possible that these two variables are actually measuring two different constructs. In the context of this study, consumers' total decision making cost actually includes two types of cost – information search cost and information processing cost. Information search cost is the cost incurred by consumers to locate the products they are looking for, while information processing cost is the cost expended by consumers to inspect the products and make a judgment about how much they like it. The total amount of time expended on decision making may be a measure of consumers' total decision making cost including both information search cost and information processing cost, while perceived decision making difficulty may be a measure of consumers' information processing cost only. The second explanation is more plausible and it also helps to explain some counter-intuitive findings.

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Contradictory to my prediction, when consumers received higher quality PPRs, they experienced more difficulty making a purchase decision. One possible explanation is that higher quality PPRs, i.e., recommendations that better match consumers' preference and taste, increase the size of consumers' consideration set, makes them examine more items, and thus, increases their information processing cost. If perceived decision making difficulty is a measure of consumer information processing cost, then, consumers will experience higher decision making difficulty when the quality of PPRs improves.

Another surprising finding is that higher quality PPRs reduce the decision making time for high knowledge consumers but increase the decision making time for low knowledge consumers. One possible explanation is that the proportion of information search cost and information processing cost are different between high knowledge and low knowledge consumers. On average, compared to low knowledge consumers, high knowledge consumers incur lower information processing cost, and a larger proportion of their total decision making cost is information search cost. When an online store recommends items that better match consumers' preferences or taste, it reduces consumers' information search cost incurred to locate those items, while at the same time increases consumers' information processing cost by increasing their consideration set. Because high knowledge consumers' decision making cost is mainly information search cost, and when the reduction in their information search cost exceeds the increase in their information processing cost, they will still experience a lower total decision making cost. The story is the opposite for low knowledge consumers. Because the reduction in their

information search cost does not offset the increase in their information processing cost, low knowledge consumers will end up incurring higher total decision making cost.

Finally, consumer decision making satisfaction turns out to be a very strong variable that links the quality of PPRs and consumer repurchase intention. It was the strongest predictor of consumer repurchase intention and could be significantly increased by offering higher quality PPRs. An interesting question is why consumers become more satisfied when receiving higher quality PPRs. In this round of pilot study, consumer decision making satisfaction was used as an alternative measure of consumer decision making quality and it had a strong correlation with consumer decision making confidence, so one possible explanation is that higher quality PPRs increase consumer decision making quality, which in turn drives consumer decision making satisfaction. Another possible explanation is that consumers become more satisfied because higher quality PPRs make their decision making process more enjoyable and consumers extract more hedonic value out of this process. Related to this, a substantial body of IS literature has found that state of flow and cognitive absorption influence users' attitude and behavior towards various information systems including websites (e.g., Agarwal and Karahanna 2000). The above two streams of research may help explain why PPRs influence consumers' decision making satisfaction. It is very possible that PPRs increase both the utilitarian value obtained by consumers in the form of a higher quality purchase decision and the hedonic value in the form of fun experienced by consumers during the decision making process.

Appendix 19. OLS Regression Results of the Final Data Collection (N=253)

Variable	Product Brokering Costs			Product Brokering Quality		Store Loyalty
	DM^a Time B (Std Error)	**Ease of DM^a** B (Std Error)	**Ease of Info Search** B (Std Error)	**DM^a Satisfaction** B (Std Error)	**DM^a Confidence** B (Std Error)	**Repurchase Intention** B (Std Error)
Quality of PPRs	36.49 (10.18) ***	-.33 (.05) ***	.41 (.05) ***	.14 (.05) **	.18 (.06) **	---
Product Knowledge	45.90 (8.23) ***	.01 (.04)	.15 (.05) **	-.02 (.04)	-.05 (.05)	---
Website Knowledge	13.14 (9.27)	.05 (.05)	.12 (.05) **	.11 (.04) *	-.08 (.05)	---
PPR X Product Knowledge	6.26 (6.40)	-.04 (.03)	-.05 (.04)	.05 (.03)	.02 (.04)	---
Website Usability	-57.47 (15.30) ***	.29(.08) ***	.24 (.08) **	.46 (.08) ***	.17 (.08) *	---
Product Information Quality	20.52 (13.59)	.03 (.07)	.09 (.08)	.16 (.07) *	.12 (.07)	---
Product Selection	60.06 (13.35) ***	.18 (.07) *	.12 (.08)	.04 (.06)	.05 (.07)	---
DM^a Time	---	---	---	---	---	.00 (.00)
Ease of DM^a						-.03 (.06)
Ease of Information Search						.03 (.05)
DM^a Confidence						.20 (.08) **
DM^a Satisfaction	---	---	---	---	---	.27 (.07) ***
Purchase Efficiency	---	---	---	---	---	.12 (.09)
Delivery Efficiency	---	---	---	---	---	.18 (.08) *
Post-sales Efficiency	---	---	---	---	---	.01 (.05)
Price Perception	---	---	---	---	---	.41 (.05) ***
DM^c Involvement	18.64 (12.64)	-.18 (.07) **	---	---	.32 (.07) ***	---
Gender	-29.45 (23.42)	.13 (.12)	.20 (.13)	.16 (.12)	.23 (.13)	-.02 (.13)
Age	-24.48 (7.67) **	-.04 (.04)	-.01 (.04)	.03 (.04)	.05 (.04)	.05 (.04)
Internet Use	-28.27 (6.53) ***	.03 (.03)	-.02 (.04)	-.02 (.03)	.08 (.04) *	.03 (.04)
Previous Experience	---	---	---	---	---	.34 (.13) **
Constant	1083.94 (180.78)	3.41 (.94)	.52 (1.05)	-.37 (.93)	.36 (1.02)	-1.47 (1.09)
R-square	32.5%	30.9%	39.8%	41.1%	29.1%	52.6%

^{a} DM – Decision Making

† significant at α = 0.1   * significant at α = 0.05   ** significant at α = 0.01   *** significant at α = 0.001

Appendix 20. Final Data Collection Questionnaire

This study is to investigate how consumers make purchase decisions at Amazon.com. Please follow the step-by-step instructions given on the screen. The whole experiment will take about 15 to 20 minutes. Thank you for your participation!!! Please raise your hand whenever you have any questions.

Now, please click the "Continue" button to start the experiment.

(Previous Experience with Amazon.com)
    (1) Have you ever purchased anything from Amazon.com before?
        Yes ___   No ___
    (2) Have you ever visited Amazon.com before (including trips with no purchases)?
        Yes ___   No ___

(Website Knowledge)
Please tell us how familiar you are with Amazon.com's website. To what extent do you agree with the following statements?

Strongly disagree   ————————▶   **Strongly agree**
       1   2   3   4   5   6   7

    (1) I am very familiar with Amazon.com's website.
       1   2   3   4   5   6   7
    (2) I am very good at using all kinds of tools to perform various purchase-related tasks at Amazon.com.
       1   2   3   4   5   6   7
    (3) I always know where I can find the products/information I am looking for at Amazon.com.
       1   2   3   4   5   6   7
    (4) I visit Amazon.com very often.
       1   2   3   4   5   6   7
    (5) I have been to Amazon.com many times.
       1   2   3   4   5   6   7

(Product Category Knowledge)
Please tell us how much you know about movies and TV shows. To what extent do you agree with the following statements?

Strongly disagree   ————————▶   **Strongly agree**
       1   2   3   4   5   6   7

    (1) I watch a lot of TV and/or movies in my spare time.
       1   2   3   4   5   6   7
    (2) I know almost all popular TV shows and/or movies.
       1   2   3   4   5   6   7

(3) I can name many Hollywood actors and directors.
    1   2   3   4   5   6   7

Your next task is to "purchase" two DVD items for yourself subject to a budget constraint. All the participants of this experiment will be automatically entered for a lottery drawing. Winners will get one or two DVDs they have picked in the experiment for free.
As the navigation bar is not available, whenever you want to return to the previous page, please right click your mouse, then click "Back".

Now, please click the "Continue" button to go to Amazon.com, then, follow the instructions on the booklet to finish the purchase.

[Insert Experimental Protocol Here]

(Quality of PPRs)
Please think about the recommended items you have just inspected. To what extent do you agree with the following statements?

Strongly disagree ⟶ **Strongly agree**
    1   2   3   4   5   6   7

(1) All the items recommended to me match my preference very well.
    1   2   3   4   5   6   7
(2) All the items recommended to me fit my taste very well.
    1   2   3   4   5   6   7
(3) All the recommended items are interesting to me.
    1   2   3   4   5   6   7
(4) I would like to buy all these items if there is no budget constraint.
    1   2   3   4   5   6   7
(5) They are exactly what I am looking for.
    1   2   3   4   5   6   7
(6) I would like to own all of them.
    1   2   3   4   5   6   7

Please recall the decision making process, to what extent do you agree with the following statements?

Strongly disagree ⟶ **Strongly agree**
    1   2   3   4   5   6   7

(Ease of Decision Making)
    (1) It was very easy for me to make this purchase decision.
        1   2   3   4   5   6   7
   (2) I had no difficulty deciding which item would be best for me.

      1   2   3   4   5   6   7

(3) Making this purchase decision was an easy task for me.
      1   2   3   4   5   6   7

(Ease of Information Search)

(1) I had no problem locating the items I was interested in at Amazon.com.
      1   2   3   4   5   6   7

(2) It was very easy for me to locate the items I was interested in at Amazon.com.
      1   2   3   4   5   6   7

(3) Locating the items I was interested in at Amazon.com was very easy.
      1   2   3   4   5   6   7

(Decision Making Satisfaction)
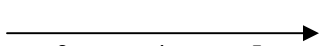
(1) I have truly enjoyed the decision making process.
      1   2   3   4   5   6   7

(2) The decision making process was fun to me.
      1   2   3   4   5   6   7

(3) I am very happy with the decision making process.
      1   2   3   4   5   6   7

(4) The decision making process was very enjoyable.
      1   2   3   4   5   6   7

(Decision Making Involvement)

(1) It is very important for me to pick the right items for myself.
      1   2   3   4   5   6   7

(2) I was very motivated to reach a good purchase decision.
      1   2   3   4   5   6   7

(3) I really want to pick the right items for myself.
      1   2   3   4   5   6   7

(Decision Making Confidence)

Please think about the items you have picked, to what extent do you agree with the following statements?

Somewhat agree ⟶ **Strongly agree**
      1   2   3   4   5   6   7

(1) I have picked the items that best fit my taste among all DVDs available at Amazon.com.
      1   2   3   4   5   6   7

(2) I have selected the items I like the most among all DVDs available at Amazon.com.
      1   2   3   4   5   6   7

(3) These two items are my favorite among all DVDs available at Amazon.com.
      1   2   3   4   5   6   7

(4) I would definitely choose the same items if I were given another chance.

1   2   3   4   5   6   7
(5) I am very satisfied with the two items I have picked for myself.
    1   2   3   4   5   6   7
(6) I am very happy that I have picked these two items.
   1   2   3   4   5   6   7

(Website Usability)
Please recall your interactions with Amazon.com's website, to what extent do you agree with the following statements?

Strongly disagree ⎯⎯⎯⎯⎯⎯⎯→ **Strongly agree**
    1   2   3   4   5   6   7

(1) The website was very user-friendly.
    1   2   3   4   5   6   7
(2) The website was easy to use.
    1   2   3   4   5   6   7
(3) The website was well organized.
    1   2   3   4   5   6   7
(4) The website was easy to navigate.
    1   2   3   4   5   6   7

(Quality of Detailed Product Information)
Please recall the detailed product information for each DVD item, to what extent do you agree with the following statements?

Strongly disagree ⎯⎯⎯⎯⎯⎯⎯→ **Strongly agree**
    1   2   3   4   5   6   7

(1) The detailed product information was very helpful.
    1   2   3   4   5   6   7
(2) The detailed product information was very useful.
    1   2   3   4   5   6   7
(3) The detailed product information was very informative.
    1   2   3   4   5   6   7

(Product Selection)
Please recall all the DVD items available at Amazon.com, to what extent do you agree with the following statements?

Strongly disagree ⎯⎯⎯⎯⎯⎯⎯→ **Strongly agree**
    1   2   3   4   5   6   7

(1) This website has a good selection of DVDs.
    1   2   3   4   5   6   7
(2) This website has a wide variety of DVDs that interest me.

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      1   2   3   4   5   6   7

(3) I could find any DVDs I like on this website.
      1   2   3   4   5   6   7

(Purchase Efficiency)
Assume you need to check out these two items, to what extent do you agree with the following statements?

Strongly disagree ⟶ **Strongly agree**
      1   2   3   4   5   6   7

(1) It should be very easy to check out these items.
      1   2   3   4   5   6   7
(2) The whole process should be very straightforward.
      1   2   3   4   5   6   7
(3) I will have no difficulty checking out these items.
      1   2   3   4   5   6   7
(4) I will not have any problem checking out these items.
      1   2   3   4   5   6   7

(Delivery Efficiency)
Assume you need to get these two items delivered to you, to what extent do you agree with the following statements?

Strongly disagree ⟶ **Strongly agree**
      1   2   3   4   5   6   7

(1) I should have no problem receiving the right items on time.
      1   2   3   4   5   6   7
(2) I am very sure that I will receive the right items on time.
      1   2   3   4   5   6   7
(3) I am very confident that I will receive the right items on time.
      1   2   3   4   5   6   7

(Post-sales Efficiency)
Assume somehow you find you have made the wrong choice after you get the items, and you need to return these two items to Amazon.com, to what extent do you agree with the following statements?

Strongly disagree ⟶ **Strongly agree**
      1   2   3   4   5   6   7

(1) I will have no problem returning the items to Amazon.com for a refund or replacement.
      1   2   3   4   5   6   7

(2) It should be very easy to return the items to Amazon.com for a refund or replacement.

    1   2   3   4   5   6   7

(3) It should be very convenient to return the items to Amazon.com for a refund or replacement.

    1   2   3   4   5   6   7

(Price Perception)

Please compare Amazon.com with other online or physical stores in terms of the prices charged for these two DVD items, to what extent do you agree with the following statements?

Strongly disagree ————————▸ **Strongly agree**

    1   2   3   4   5   6   7

(1) The prices charged by Amazon.com for these two items are very reasonable.

    1   2   3   4   5   6   7

(2) Amazon.com is offering a good deal on these two DVD items.

    1   2   3   4   5   6   7

(3) Amazon.com is offering the lowest prices for these two DVD items.

    1   2   3   4   5   6   7

(Repurchase Intention)

According to this particular shopping experience, to what extent do you agree with the following statements?

Strongly disagree ————————▸ **Strongly agree**

    1   2   3   4   5   6   7

(1) I will consider Amazon.com the first choice to buy similar products in the future.

    1   2   3   4   5   6   7

(2) I will buy more similar products at Amazon.com in the future.

    1   2   3   4   5   6   7

(3) I will come back to Amazon.com to buy similar products in the future.

    1   2   3   4   5   6   7

(Demographic Information)

Now, please tell us a little bit about yourself.

(1) What is your gender? Male _____   Female _____

(2) How old are you? _____

(3) How many years have you been using computers? _____

(4) On average, how many hours do you use computers every day? _____

(5) How many years have you been using the Internet? _____

(6) On average, how many hours do you spend on the Internet every day? _____

(7) How many years have you been purchasing online? _____

(8) How often do you purchase online (in number of orders per year)? _____

Finally, please go to the last page of your booklet and follow the instructions there to provide necessary information for the lottery drawing.

Your name will be given to the professor to get the extra credit. Winners of the lottery drawing will be notified via email in two weeks.

Thank you very much for your participation!

Survey Number:

Consumer Decision Making at Amazon.com

April, 2005

Please enter your group number shown below to log on. Then, follow the instructions on the screen to finish the study.

Please DONOT click the "Clear Data" button when you log in.

Subject ID: _____

Step 1 –
Now, at Amazon.com's homepage, please sign in to Amazon.com by clicking the "click here" as shown below.
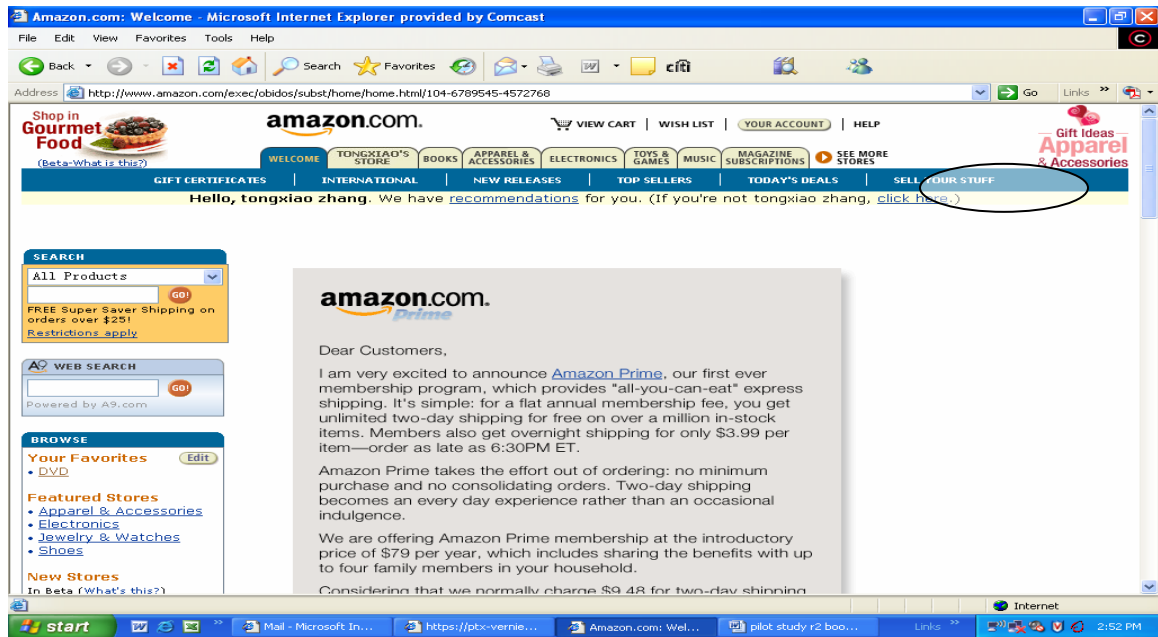
Now, please enter the fake email and password assigned to you (given below), then, click the "Sign in using our secure server" button.

Your email address: cathyamazon ⓐyahoo.com
Your password: cathyamazon
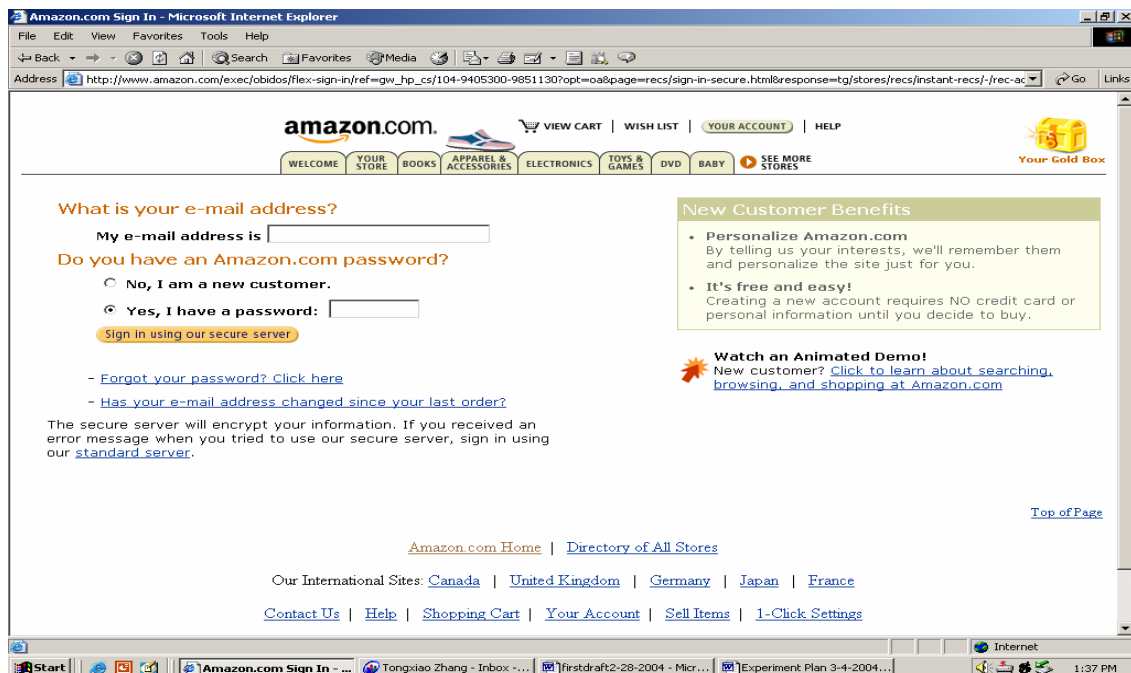
Step 2 –

Now, please spend as much time as you want to browse the website and select **two** DVDs for yourself assuming you have a **$50** budget.

Please do NOT rate any items during the purchase process and do NOT check out any items.

After you have made up your mind, please write down the items you have picked (please PRINT)

Item 1 _____   Price: $_____

Item 2 _____   Price: $_____

Between these two items, which one do you like the best? (Please check **ONLY ONE**)

Item 1 _____   Item 2 _____

Step 3 –

Please go back to Amazon.com's homepage by click Amazon.com's icon on the top of the current page.

Now, please click the "recommendations" link and inspect the top 15 items displayed on the screen (inspect all the items if less than 15).

Step 4 –

Now, please click the "Continue" button on the lower right hand corner of your screen to exit Amazon.com's website to finish the rest of the study.

Lottery Drawing Information Sheet

Now, please follow the instructions below to record the DVD items you want to get if you win the lottery. All the information collected on the Purchase Record Sheet will be used for the lottery drawing only and after this experiment, this sheet will be detached and kept separate from your experiment booklet to make sure that your name will not be identified at any time during the data analysis.

All the participants in this experiment will be automatically entered for a lottery drawing. There are **20 first-prize winners**, who will get both the two DVD items he/she has picked in the experiment for free, and **50 second-prize winners**, who will get one of the two DVD items he/she has picked for free. The winners will be notified via email within two weeks after the experiment.

If you win the first-prize, you will get both the two items you have written down on page 2 of this booklet for free. If you win the second-prize, you will get the item you like the best for free.

Please write down your name and email as clearly as possible to ensure you get notified on time.

Your Name (Please PRINT)

_____

Your Email (Please PRINT)

_____

You are done! Thank you so much for your support!!!

Please contact Tongxiao (Catherine) Zhang at tzhang@rhsmith.umd.edu if you have any questions about the study.

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