MIS Quarterly

RESEARCH ARTICLE

THE VALUE OF IT-ENABLED RETAILER LEARNING: PERSONALIZED PRODUCT RECOMMENDATIONS AND CUSTOMER STORE LOYALTY IN ELECTRONIC MARKETS[1]

Tongxiao (Catherine) Zhang
Gatton College of Business and Economics, University of Kentucky
Lexington, KY 40506-0034 U.S.A. {tzhan2@email.uky.edu}

Ritu Agarwal and Henry C. Lucas, Jr.
Robert H. Smith School of Business, University of Maryland,
College Park, MD 20742-1815 U.S.A. {ragarwal@rhsmith.umd.edu} {hlucas@rhsmith.umd.edu}

Recent research has acknowledged the key role of information technology in helping build stronger and more enduring customer relationships. Personalized product recommendations (PPRs) adapted to individual customers' preferences and tastes are one IT-enabled strategy that has been widely adopted by online retailers to enhance customers' shopping experience. Although many online retailers have implemented PPRs on their electronic storefronts to improve customer retention, empirical evidence for the effects of PPRs on retention is sparse, and the limited anecdotal evidence is contradictory. We draw upon the household production function model in the consumer economics literature to develop a theoretical framework that explains the mechanisms through which PPRs influence customer store loyalty in electronic markets. We suggest that retailer learning that occurs as a result of customer knowledge obtained to enable personalization influences the efficiency of the online product brokering activity. Data collected from a two-phase lab experiment with 253 student subjects where the quality of PPRs was manipulated are used to empirically test the predictions of the theoretical model. Empirical analyses of the data indicate that retailer learning reflected in higher quality PPRs is associated with lower product screening cost, but higher product evaluation cost. We further find that higher quality PPRs are associated with greater value derived by consumers from the online product brokering activity in terms of higher decision making quality, which is positively associated with repurchase intention. The paper presents the implications, limitations, and contributions of this study along with areas for future research.

Keywords: Personalized product recommendations, recommender systems, household production function, retailer learning, laboratory experiment, online product brokering

[1]Joe Valacich was the accepting senior editor for this paper. Mun Yi served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

Introduction

The significance of the Internet as a channel for retail commerce is now widely acknowledged. Data show that the annual growth in retail Internet sales had been strongly and consistently in the double digits until 2008, the beginning of an economic recession. According to the Census Bureau of the Department of Commerce (2008), the estimate of U.S. retail e-commerce sales for 2007 was $136.4 billion, an increase of 19 percent from 2006, while total retail sales increased 4 percent in the same period.

In the early days of e-commerce, it was believed that building customer store loyalty was more difficult online than offline. Subsequent studies challenged this assertion, finding contrary to traditional wisdom that the electronic market is more concentrated than the traditional market. Across many product categories, a few online firms dominate the market and command price premiums (Brynjolfsson and Smith 2000; Latcovich and Smith 2001). These findings raise the fundamental question of why online retailers are able to retain their customers when consumer information search and switching costs are relatively small online compared to offline. Not only does the consumer avoid the physical effort required to travel to an alternate store, information search and price comparisons at competing stores are significantly easier online (Bakos 1997).

One plausible explanation for retailers' ability to retain online customers is that although the products offered off- and online may be homogeneous, services are not. Advances in information technology offer online retailers the opportunity to improve customer retention by providing a variety of value-added services that extend beyond simply the product customers seek. Personalization has been widely adopted by online retailers to enhance their customers' shopping experience in hopes of building a strong and enduring customer relationship. The focus of this study is on one such service: information personalization through product recommender systems.

Although retailers are able to offer a larger variety of products and a greater amount of information to their customers online than they could offline, they may not necessarily generate more value for customers if consumers' information search and processing costs online are as high as or higher than in the physical channel. Information overload or choice overload has been cited as one major reason why online consumers tend to perform very limited prepurchase information searches, which frequently leads to suboptimal purchase decisions (Alba and Hutchinson 1987; Haubl and Trifts 2000). Information personalization, or adapting product information to individual consumer's needs, is an important step toward alleviating consumers' information overload. The broad 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 et al. 2003). Offering real-time personalized product recommendations (PPRs) is one important form of information personalization implemented by online retailers.

In spite of the fact that an increasing number of retailers now offer PPRs, their value for consumers and retailers is still an open question. 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 8 percent of surveyed consumers believe that personalization increases their repeat visits to content, news, or entertainment Web sites, whereas a majority of consumers stated that other types of basic site improvements would make them buy or visit Web sites more often: 54 percent cited faster-loading pages and 52 percent cited better navigation. Because building and operating a personalized Web site costs over four times more than operating a comparable dynamic site (Jupiter Research 2003), the value potential of personalization in general and PPRs in particular is a critical issue for research. The purpose of this study is to address an important, unanswered question about PPRs: Do PPRs generate value for online retailers, and if so, how? In other words, our goal is to theorize and empirically test the mechanism underlying the value that online retailers can derive from PPRs.

To understand this mechanism, we draw upon the theoretical foundations of the household production function model described in the consumer economics literature (Ratchford 2001) and research examining online consumer search and information processing strategies. We adapt and extend this model, originally developed to explain consumer brand loyalty, to theorize about the effects of online retailer learning, manifest in the form of higher quality PPRs, on consumer store loyalty. We test our predictions using a unique experimental design where we manipulate the quality of a retailers' learning, thereby inducing variation in the quality of PPRs offered.

The rest of the paper is structured as follows. First, we review existing literature in related areas and propose a conceptual model that explains how personalized services in general influence customer store loyalty. Next, building upon this conceptual model, we develop a research model to investigate the impact of PPRs on customer store loyalty. Then, we describe the methodology used to empirically test the model. Finally, we report the results of the empirical study, discuss its implications, contributions, and limitations, and suggest directions for future research.

Theoretical Background

The broad stream of literature into which this study fits is related to the business value and impacts of IT. The influence of a variety of information technologies on firm performance outcomes such as sales, internal operations, procurement, market share, and return on assets has been investigated by IS researchers (e.g., Hitt and Brynjolfsson 1996; Zhu and Kraemer 2005). An extensive review of this literature is beyond the scope of this paper and is available in Melville et al. (2004). One notable gap in this research, pointed out by Ray et al. (2005, p. 626), is that "empirical research examining the link between IT and customer service performance has been lacking" although "customer service has emerged as a strategic imperative for most firms." Drawing upon the resource-based view, Ray et al. examined the effects of various IT resources and capabilities on the performance of the customer service process across 72 life and health insurance firms in North America. They found that shared knowledge between IT and customer service units is a key IT capability that affects customer service process performance; it moderates the impacts of explicit IT resources such as generic information technologies and IT spending. These researchers also found that generic information technologies and IT spending do not have significant direct impacts on customer service process performance. Consistent with the resource-based view, they conclude that in a mature market, only tacit, socially complex, and firm-specific resources can endow firms with sustained competitive advantage. This study provides compelling theoretical and empirical evidence that IT plays a significant role in enabling firms to offer superior services and ultimately build stronger relationships with their customers. However, their findings also underscore the notion that it is not IT *per se*, but rather what the firm does with IT, in conjunction with other valuable and rare resources, that generates value. Personalization is one such IT-based strategy that couples technological capabilities with customer knowledge to provide superior value to customers.

Personalization

Personalization is defined as the design, management, and delivery of content and business processes to users, based on known, observed, and predictive information (Meister et al. 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. Murthi and Sarkar's (2003) comprehensive review of previous studies on personalization classifies previous research into two streams: (1) personalization process and (2) personalization and firm strategy. The first stream focuses on the technical issues associated with personalization, while studies in the second stream investigate the strategic impact of personalization on firm performance.

Our research is most closely aligned with studies in the second stream. The general conclusion drawn from prior work is that the reduction in consumers' information search cost leads to an increase in consumers' power relative to the firm, but that effective personalization strategies can help reverse this shift. The majority of the work in this stream has adopted an analytical modeling approach. To reach a better understanding of the strategic value of personalization to firms, empirical research is needed to validate the assumptions and the results of the analytical models (Murthi and Sarkar 2003). In this study, we focus on one form of personalization: information personalization, more specifically, PPRs (personalized product recommendations). Because improving customer *store loyalty* (i.e., repeat visits and purchases) has been cited as a major motivation underlying online retailers' decision to offer PPRs, we examine, both theoretically and empirically, how PPRs influence this important outcome.

The notion that personalized recommendations in online settings influence outcomes for consumers and firms has also been acknowledged in recent information systems literature. Xiao and Benbasat (2007) conducted an extensive literature review to develop a comprehensive conceptual model and propositions about how the characteristics of recommendation agents and their use influence future use of the recommendation agent. They propose that key intervening variables in this relationship are the user's decision-making process and user evaluations of the recommendation agent, reflected in constructs such as trust, perceived usefulness, etc. The paper is conceptual and the authors did not undertake an empirical test of their model.

Hostler et al. (2005) focus attention on the importance of purchase efficiency generated through technology-based interventions, albeit in a different context. They examine the influence of shopbots on purchase efficiency in an experimental setting. Shopbot technology is distinct from PPRs in that the shopbot requires real-time information from the consumer about specific products of interest, while a personalized recommender system analyzes consumers' implicit and explicit preferences from the past to proactively recommend items that may be of interest to the consumer. Other related work includes that of Kumar and Benbasat (2006), who found that the provision of recommendations and consumer reviews on Amazon increased both the usefulness and social presence of the website. Finally, Tam and Ho (2003) found that subjects receiving personalized recommendations downloaded music files more frequently.

Although previous studies have examined recommendation agents or shopbots from various perspectives, no work we are aware of has provided and empirically tested a theoretical framework that explains why and how the quality of PPRs influence consumer store loyalty, which is the focus of our study.

The Antecedent of Store Loyalty: Consumer Shopping Efficiency

The theoretical logic for understanding how personalization influences customer store loyalty may be found in the consumer economics literature. Ratchford (2001) discusses the integration of a human capital model and household production model in consumer economics (Becker et al. 1994; Becker and Murphy 1988; Stigler and Becker 1977) that provides unique insights into the role of investments in knowledge in explaining a variety of consumer behaviors, including 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, p. 397). In the household production model, the household or consumer is viewed as a small business combining goods, time, and human capital to produce either physical goods or intangible goods (services or experiences) for its own consumption (Ratchford 2001). Examples of this output might be meals produced and consumed in the household or experiences associated with listening to classical music. Consumers seek to maximize the efficiency of their production process, that is, to maximize the output or the utility obtained from it and to minimize the input or the cost incurred to engage in the activity.

Applying this framework to explain consumers' brand loyalty, Ratchford (2001) argues that whenever a significant amount of human capital is required for consuming a product or a service, the efficiency of the process varies across individual consumers due to the different amounts of human capital they possess. Consumers accumulate human capital each time they use a brand, the additional human capital associated with that brand makes consumers' future consumption of the same brand more efficient, and thus, brand loyalty develops. As Ratchford observes,

> the analysis....predicts that brand loyalty should increase with experience at using a brand...when brand-specific knowledge is *important in using* a brand efficiently one would generally expect *brand loyalty* to be high (p. 407).

Ratchford presents the example of producing a cake to illustrate the creation of brand loyalty. Making a cake at home requires time and skill from the baker as well as materials, such as cake mix and other ingredients, and equipment (an oven). After using the same cake mix repeatedly, the baker is able to memorize the recipe. She is able to make the cake more efficiently and with less cognitive effort, and at the same time, obtain the best quality from the ingredients. The extra brand-specific skill 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.

Analogously, we argue that the household production model can also be applied to explain consumers' store loyalty in an electronic market. Online shopping can be viewed as a household production process that requires a significant investment of human capital, mainly product knowledge and website knowledge (familiarity with the interface of an online store's website), in completing a series of purchase-related tasks. Consumers exhibit loyalty to a specific online store because it is more efficient for them to undertake the purchase at this online store compared with competing ones. Therefore, just as consumers' brand loyalty is driven by the efficiency of the production process, consumers' store loyalty online is driven by the efficiency of the online shopping process.

Consumer Learning, Retailer Learning, and Consumer Shopping Efficiency

Shopping is a joint production process that involves both consumers and retailers. To the extent that shopping requires significant investments in human capital, in general, consumers' shopping efficiency can be maximized through a *learning* process. Two types of learning occur simultaneously each time a consumer shops in a retail store: consumer learning and retailer learning.

Consumer Learning

Consumer learning is a process whereby 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

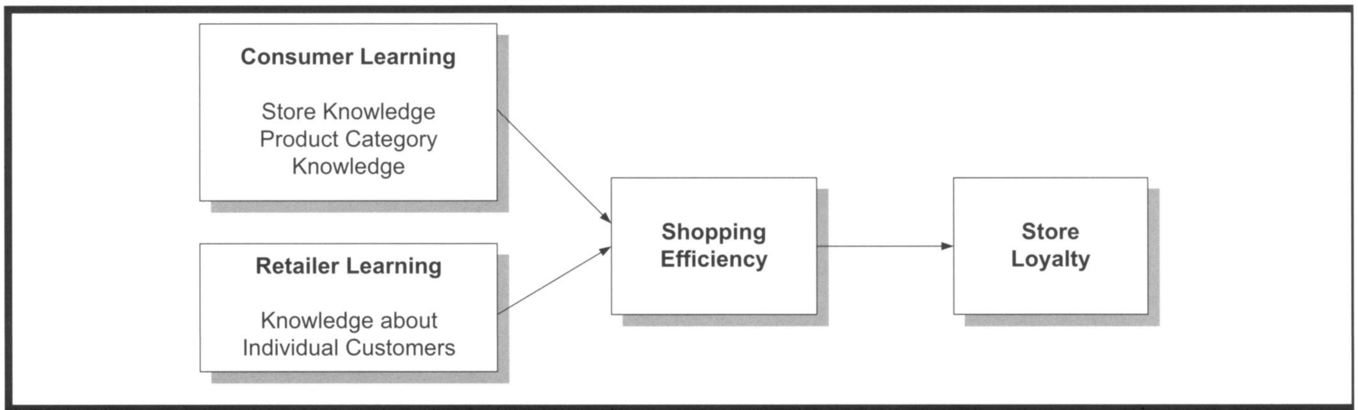

Figure 1. Conceptual Model

knowledge that enables a consumer to perform product-related tasks successfully (Alba and Hutchinson 1987). A significant body of literature has demonstrated the powerful effects of repetition on consumers' performance of various tasks (e.g., Einhorn and Hogarth 1987; Hoyer 1984; Payne 1976; Russo and Dosher 1983). A general conclusion from this research, consistent with the learning and skill acquisition literature (Bower and Hilgard 1981), is that tasks are performed more rapidly and make smaller demands on cognitive resources after more repetitions.

Two types of consumer knowledge are salient in the context of shopping: product knowledge and store knowledge. While the importance of product knowledge on consumers' purchase decision making is well documented in the literature (e.g., Holyoak 1984; Sternberg 1986; Weisberg and Alba 1981), with the exception of Park et al. (1989), less attention has been focused on how consumers' shopping behaviors are influenced by their store knowledge. In Park et al.'s 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" (p. 423). This research found that consumer store knowledge affects information search patterns in a store as well as the extent to which brand choices are influenced by the stimuli in the shopping environment. Just as store knowledge is essential to shop at physical stores, website knowledge is arguably even more necessary for consumers to shop online. Each time consumers shop at an online store, they become more familiar with the online store's website interface and, thus, are able to complete various purchase-related tasks with greater speed and ease. The amount of consumers' website knowledge accumulated through a learning process can significantly influence online shopping efficiency.

Retailer Learning

In contrast to consumer learning, retailer learning has not been formally defined in the literature. Adapting the definition of consumer learning, we define retailer learning as a process whereby retailers accumulate knowledge about individual customers through repetitive interactions. It is almost a truism that knowledge of one's customer is a precondition for a successful enterprise. The emergence of the Internet has made the collection and analysis of a large volume of individual consumer information automatic and effortless (Walsh and Godfrey 2000), thereby significantly increasing the efficiency with which retailers can learn about consumer preferences and tastes, which then enables retailers to offer more personalized services and better meet individual consumers' specific needs. Therefore, we argue that the level of personalized services offered by online retailers has a direct impact on consumers' online shopping efficiency.

Based on the literature reviewed above, Figure 1 represents our conceptualization of the mechanism through which personalized services affect consumer store loyalty. Personalization is a reflection of retailer learning that, in conjunction with consumer learning, enhances the efficiency of the shopping activity. Following from the consumer economics literature, efficiency maximizing consumers will display a propensity to engage in activities that are more efficient (i.e., they will exhibit store loyalty).

Research Model and Hypotheses

Our specific interest is in investigating how one particular form of personalized service offered by online retailers, PPRs,

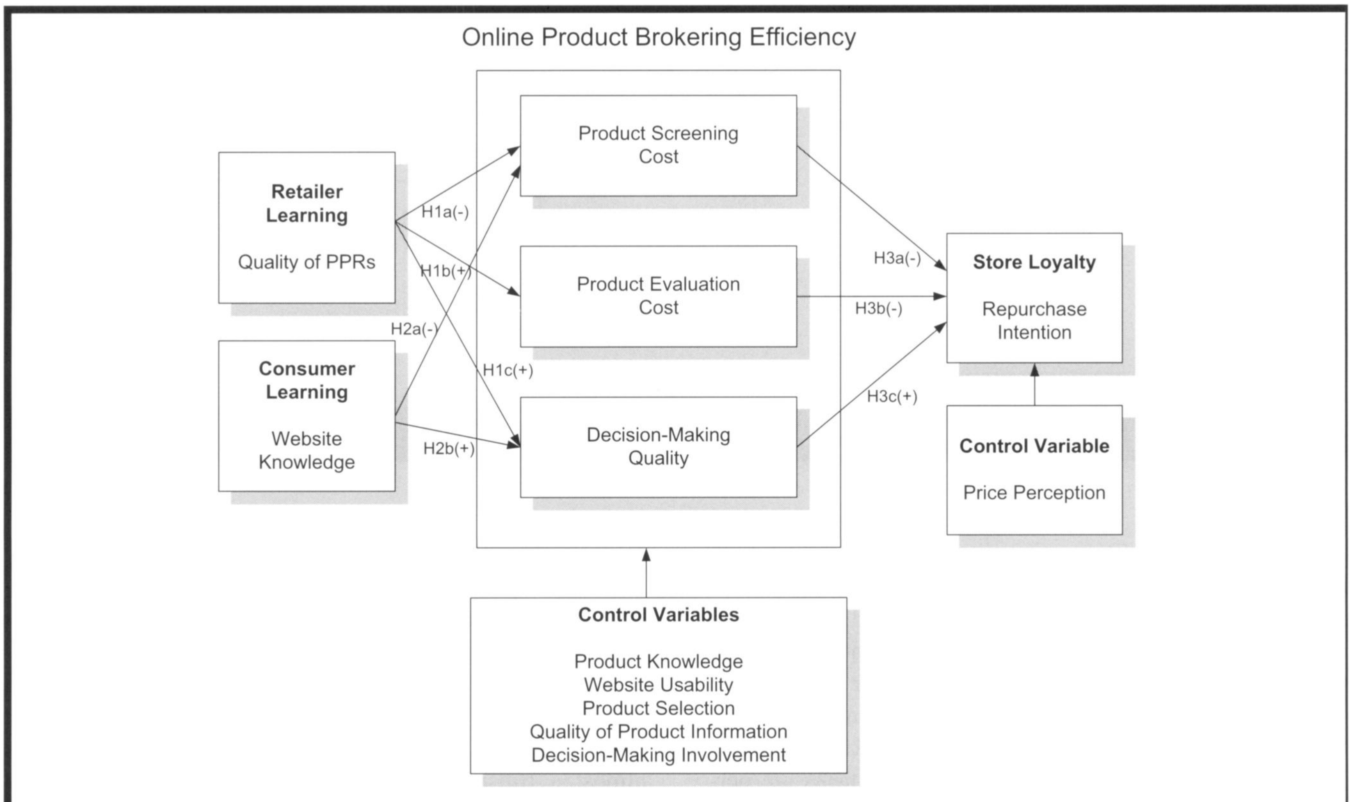

Figure 2. Research Model

influences consumer store loyalty. To examine the role of PPRs, we propose the research model in Figure 2. The mechanism linking customer and retailer learning to online store loyalty is online product brokering efficiency, reflecting the efficiencies created for the consumer. We predict that higher quality PPRs, an instantiation of retailer learning, in conjunction with consumer learning, increase consumer online product brokering efficiency, which in turn improves customer store loyalty, operationalized as repurchase intention. Past research has conceptualized the consumer's shopping process as 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 et al. 1998). We focus on consumer product brokering efficiency because product brokering is the stage in which consumers engage in information search and processing to decide which product to purchase to meet their specific needs, and is therefore the shopping stage where PPRs are likely to have the greatest impact. In addition, we introduce a variety of controls in the model to account for factors that may influence the mediating and dependent variables but are not of theoretical interest in this study.

Consumer Online Product Brokering Efficiency

The central construct in the research model, *consumer online product brokering efficiency*, is based on the household production model and defined as the costs and the value of the online shopping activity for the consumer. Product brokering is one of several stages a consumer goes through in completing an online shopping task, and it is the stage where we suggest PPRs have the most direct and strongest impact. The input to the brokering process is the consumer's effort expended on screening and evaluating various items for purchase and the output is the purchase decision. Consumer product brokering effort is typically comprised of two stages: a product screening stage and a product evaluation stage (Payne 1982; Payne et al. 1988). Therefore, as depicted in Figure 2, we assess consumer product brokering cost using two components: product screening cost and product evaluation cost. The value obtained by consumers during the product brokering process is defined as the quality of the purchase decision (i.e., the extent to which the items consumers have decided to purchase fit their needs or taste). As shown in Figure 2, we theorize that both retailer learning and consumer learning affect components of consumers' online product brokering efficiency, and we evaluate efficiency from both the input (product screening and evaluation cost) and the output (decision-making quality).

Retailer Learning: Quality of PPRs and Online Product Brokering Efficiency

Retailer learning captures how much knowledge the retailer has about individual consumers and is reflected in the quality of PPRs generated for each consumer. The quality of PPRs, defined as how closely the recommended products match individual consumers' preferences, is expected to significantly influence online product brokering efficiency.

As observed extensively in the consumer information search and decision-making literature, consumers adapt their decision-making strategies to specific situations and environments (Payne 1982). In complex environments, consumers are often unable to evaluate all of the 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 and product evaluation (collectively, product brokering) (Payne 1982; Payne et al. 1988). First, at the product screening stage, consumers screen a large set of relevant products, without examining any of them in great depth, and identify a subset that includes the most promising alternatives, labeled a *consideration set*. Subsequently, at the 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).

Alba et al. (1997) point out that the most important benefit of online shopping to consumers is electronic screening. They assert that without screening, there is limited value to the consumer of having access to a dramatically increased pool of options on the Internet. Other researchers make similar observations: "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 et al. 2003, p. 57). At the product screening stage, with accumulated knowledge about individual consumers, a recommender system can potentially undertake "resource-intensive but standardizable information search and processing tasks" on behalf of consumers (Haubl and Trifts 2000, p. 6). When the recommender system has a utility function that is close to that of a consumer, it can sort through thousands of options and narrow the alternatives to a handful that best match the utility function of the consumer. Therefore, higher quality PPRs lower consumers' product screening costs by saving them the effort of directly inspecting information on products with low likelihood of being chosen (Diehl et al. 2003).

In contrast, higher quality PPRs can *increase* consumer product evaluation cost by enlarging the size of the consumer's consideration set. A study by Pereira (2001) found that when interactive decision aids are available, consumers tend to include more items in their consideration set. He argues that because the decision aid performs 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. Given fixed information processing speed and all else being equal, evaluating more items will result in higher product evaluation costs.

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

H1a: Higher quality PPRs are associated with lower consumer product screening cost.

H1b: Higher quality PPRs are associated with higher consumer product evaluation cost.

The quality of PPRs also has a strong impact on the amount of value consumers acquire from the online product brokering activity (i.e., on consumer decision-making quality). Because higher quality PPRs save consumer information search and processing costs at the product screening stage, decision makers can apply the freed resources to performing in-depth assessments at the product evaluation stage, thereby reaching more informed purchase decisions. Moreover, with limited time and cognitive resources during screening, the average consumer is not able or not willing to search an entire database exhaustively to locate the items that best match his/her preference, which may prevent him/her from forming a high quality consideration set. By searching the whole database on behalf of individual consumers, recommender systems are able to locate items that consumers like but cannot find on their own and assist in forming a higher quality consideration set for further evaluation, which then results in a higher quality purchase decision. Therefore, we test

H1c: Higher quality PPRs are associated with higher consumer decision-making quality.

Consumer Learning: Website Knowledge and Online Product Brokering Efficiency

In the conceptual model we noted that consumer learning includes store knowledge and product knowledge, both representing important drivers of the efficiency of the shopping activity. Because our focus in the research model is on online shopping, we use website knowledge as the operationalization of the store knowledge construct, and include product knowledge[2] as a control in the model.

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 et al. 2003; Kahn and McAlister 1997). It takes a significant amount of time and effort to find products when going to a retail store for the first time or when the layout of a store has changed, but it becomes easier with repeated shopping trips. The situation is more complex in the context of online shopping. Electronic technology renders the 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 IT (Cho and Park 2001).

There is considerable evidence to suggest that the layout of online stores varies significantly, and this layout influences consumer search behaviors and outcomes. Griffith (2005) classified these layouts into two categories: tunnel structured, which constricts a consumer's movements through a web site to predetermined paths, and tree structured, which allows consumers to move freely and access information easily. This study found that online store layout has a significant impact on consumers' information processing, purchase intentions, and attitude toward the retailer. According to the conventional retailing store layout theory (e.g., Ghosh 1994; Mason et al. 1991), there are three major types of store layouts: grid, freeform, and racetrack/boutique. Vrechopoulos et al. (2004) transformed this typology into the virtual setting and found that online stores' layout significantly affects consumer behavior such as the length of time expended on the website. With a sample of 551 retail websites from six different countries around the globe, Vrechopoulos, Papamichail, and Doukidis (2002) found that the freeform layout is employed by 51.3 percent of the investigated websites, while grid and racetrack layouts are employed by 21.2 and 1.5 percent of the sites respectively, and the rest (26 percent) cannot be classified into any of the three categories.

Because a large amount of product information is usually 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 can be 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 allows them to perform information search and processing more efficiently at the product screening stage by saving a significant amount of time and cognitive effort in navigating the website. The freed time and cognitive resources can be devoted to more in-depth information processing at the product evaluation stage, increasing the consumer's chance of making a higher *quality* purchase decision.

Using the media metrix panel data, Johnson et al. (2003) found that the consumer's website visit duration declines the more frequently 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 the researchers did not control for other possible factors that may also influence the consumer's site visit duration, their study does not provide direct and strong evidence that the decline in site visit duration is due to consumer learning. Moreover, when evaluating consumers' shopping efficiency, only the cost incurred by consumers was considered and the value derived by consumers from the process was not incorporated into the equation and, therefore, the impact of consumers' website knowledge on their shopping efficiency remains unanswered. Based on the above discussion, we propose the following hypotheses:

H2a: Higher website knowledge is associated with lower consumer product screening cost.

H2b: Higher website knowledge is associated with higher consumer decision-making quality.

Note that we do not hypothesize a relationship between consumer website knowledge and product evaluation cost because, theoretically, there is no reason to expect that better knowledge about how the website is designed would aid consumers in evaluating the competing products in their consideration set.

[2]As noted in the discussion about the conceptual model, product knowledge has also been empirically examined in a significant body of prior research.

Online Product Brokering 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 on this phenomenon. Online shopping is the value-adding outcome of a household production process that utilizes human capital as a key input. Following Ratchford, we suggest that consumer store loyalty online is driven by the efficiency of the shopping process (i.e., the utility maximizing consumer will be more loyal to stores that offer higher shopping efficiency). As discussed earlier, because consumers go through multiple stages to complete their shopping activity—need recognition, product brokering, purchase, delivery, and post-sales service—shopping efficiency at each of these stages should have a positive impact on consumer store loyalty. Here we focus on the product brokering stage because it is the stage that PPRs directly impact. Recall that consumer online product brokering efficiency is defined as the costs incurred and value derived from online product brokering. Therefore, higher decision-making quality, lower product screening cost, and product evaluation cost result in higher online product brokering efficiency, and ultimately higher customer store loyalty. Based on this, we test the following hypotheses:

H3a: Lower consumer product screening cost is associated with higher consumer store loyalty.

H3b: Lower consumer product evaluation cost is associated with higher consumer store loyalty.

H3c: Higher decision-making quality is associated with higher consumer store loyalty.

Controls

To account for other influences on the core dependent and mediating variables, we include a robust set of controls in the research model. As noted in the discussion of the conceptual model, we included product knowledge as a control variable since greater knowledge of products should make product brokering more efficient. Further, because in addition to PPRs, other website characteristics may also affect consumer online product brokering efficiency, we measured consumers' subjective evaluation of website usability (Wolfinbarger and Gilly 2003), product selection (Zeithaml et al. 1996), and quality of product information (McKinney et al. 2002) as control variables for consumer online product brokering efficiency. Here product information refers to the detailed information presented to online shoppers at Amazon.com about a specific DVD item, which usually includes a picture of the item, its description, editorial reviews, and customer reviews. The impact of feedback mechanisms such as customer reviews on consumers' shopping behavior in electronic markets has been receiving increasing attention in IS research (e.g., Pavlou and Dimoka 2006; Pavlou and Gefen 2005). Because customer reviews can be an important information source for online shoppers and directly influence their product brokering efficiency when they are inspecting items with which they have no first-hand consumption experience, we control for quality of product information.

In addition, previous studies (e.g., Beatty and Smith 1987; Slama and Tashchian 1985; Smith and Bristor 1994) have consistently shown that purchase or decision-making involvement has a strong impact on consumers' information search and decision-making behavior, including the amount of effort expended on information search and processing. Therefore, this involvement should be controlled for in the model for consumer online product brokering efficiency. Finally, price perception was also controlled as an influence on customer store loyalty because it has been found to have a strong effect on consumer repurchase intention (e.g., Jiang and Rosenbloom 2005; Liu and Arnett 2000).

Methodology

We tested the research hypotheses through an experiment using two groups of subjects that completed an online shopping task on Amazon.com. The experimenter provided different levels of information to Amazon's recommender system for each group, thereby assuring that each group received different quality PPRs. During the online shopping task, users' interaction with the website was automatically captured. After task completion, we measured various research constructs through a survey. Details of the procedure, including the operationalization of the manipulation and measurement of variables are provided below.

Target Website and Product Category

As a leader in implementing personalization technologies (Kumar and Benbasat 2001), Amazon.com was selected as the target website. The selection of Amazon as opposed to a fictitious retailer was also motivated by our desire to provide a degree of realism to the experimental set-up. We chose DVDs as the target product category. DVDs are one of the first product categories for which Amazon.com started offering PPRs. Thus, personalized recommendations for DVDs are very familiar to Amazon.com's consumers. A small-scale survey among business school students also indicated that DVDs are one of the most frequently purchased products at Amazon.com among college students.

Manipulation to Achieve Variance in the Quality of PPRs

Results of a small-scale survey among business school students revealed two main problems that made a simple survey infeasible for data collection. First, many students who had shopped at Amazon.com did not have an account and had never received PPRs; therefore, they were unable to evaluate the quality of PPRs. Moreover, among those who had received PPRs, many rated the quality of PPRs as poor because they had made a very limited number of purchases at Amazon.com for products in the same category, and they never rated any products. Without sufficient input from individual customers in the form of either previous purchases or product ratings, recommender systems cannot generate high quality PPRs to individual customers (i.e., retailers are unable to learn about their consumers). If we simply used a survey to collect the data, we were not guaranteed sufficient variance for the core variable in the model—the quality of PPRs—with a reasonable sample size. Therefore, we decided to manipulate the quality of PPRs and collect the data through an innovative lab experiment.

Because the quality of PPRs is directly influenced by the level of consumer input given to the recommender system, the main manipulation in the experiment is the amount of consumer input provided to the recommender system. 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). The recommender system at Amazon.com mainly receives two types of input from individual consumers: purchases and product ratings. Because subjects cannot make any real purchases in the study, the only type of input we manipulate is the number of product ratings. Thus, we are able to manipulate the quality of PPRs generated by the recommender system, keeping all other features of the recommender system constant.

In the study, we first collected subjects' product ratings; next, we created a fictitious account for each subject at Amazon.com and entered different numbers of product ratings to each account: 5 product ratings (low input) or 15 product ratings (high input). All subjects were then required to log on to their account to complete a simulated purchase task. Results of the pilot studies showed that 5 product ratings and 15 product ratings are the two input levels that can successfully make the recommender system at Amazon.com produce PPRs with significantly different quality and, therefore, generate sufficient variance for the core variable in the model: the quality of PPRs.

Experimental Procedures: Pilot Tests

Prior to conducting the regular data collection, we completed three pilot tests. The purpose of the pilot tests (with 51, 43, and 59 subjects, respectively) was to ensure that the manipulation was anchored at the right level to be able to detect differences, to refine the data collection procedures, and to assess the psychometric properties of the measures.

In the first round pilot study, all the subjects were randomly assigned to four treatment groups (minimum input = 5 product ratings, low input = 10 product ratings, medium input = 15 product ratings, and high input = 30 product ratings) and they finished a simulated purchase task at home by following the instructions on the questionnaire. The subjects first logged on to a fictitious account at Amazon.com with assigned login and password, and rated the required number of DVD items. Then, they were asked to complete a simulated purchase task and fill out a survey based on this shopping experience. The subjects recorded the time when they started decision making and when they were finished. The results of one-way ANOVA showed that the mean of the quality of PPRs increased from group 1 to group 4, as predicted, but the difference was not statistically significant.

In the second round pilot study, we made two major changes to the data collection procedures. First, all of the subjects evaluated the quality of PPRs *after* they made the purchase decisions to prevent the evaluation of PPRs from interfering with subjects' normal decision-making process. In addition, the data collection was conducted in *two phases*. In phase I, all subjects were given a list of Amazon.com's 100 top seller DVDs to rate all of the items they had watched before. Then, we created a fictitious 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, subjects finished a simulated purchase and filled out the survey in a computer lab.

In the first two pilots, 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 by creating a correlation between consumers' product knowledge (i.e., number of DVD items they had watched) and the quality of PPRs they received. Our solution was first to screen all of the subjects and drop those who had not watched a sufficient number of items (i.e., the number set for the group with the highest input level) and then randomly assign the rest of the subjects to different treatment conditions. A drawback of this solution is that we may lose many subjects if we set the bar too high, that is, the number of product ratings required for the highest input group is too large, so it is critical for us to find the minimum number of product ratings required by the highest input group to generate significantly higher quality PPRs than the low input group. The results of the second pilot study show that the quality of PPRs was significantly different between the 15-product rating and 5-product rating groups, but no significant difference was found between the 5-product rating and 10-product rating groups, nor between the 15-product rating and 30-product rating groups. This finding indicates that two input levels should be sufficient to generate significantly different quality PPRs. The minimum number of product ratings the high input group needs to produce significantly higher quality PPRs is 15 and, therefore, we decided to limit the treatment conditions to only two levels—high input (15 product ratings) and low input (5 product ratings)—in the next round of pilot study.

In the third round pilot study, after the subjects' product ratings were collected in pase I, we screened out subjects who had watched fewer than 15 items, and then randomly assigned the rest of the subjects to one of the two treatment conditions. Consistent with our prediction, the results of one-way ANOVA showed that subjects in the high input group perceived the quality of PPRs to be significantly higher than subjects in the low input group.

We evaluated and refined the psychometric properties of all of the measurement scales during the pilot studies; details are available from the authors.

Experimental Procedures: Main Experiment

Based on the findings from the pilot tests, we designed the main experiment as a two-phase task. In phase I, we provided the subjects with a list of 134 of Amazon.com's top seller DVDs on paper and asked them to rate all of the items they had watched before. After we collected the subjects' product ratings, we dropped those who rated fewer than 15 items from the sample and randomly assigned the rest of the subjects to two treatment conditions: high input condition (15 product ratings) and low input condition (5 product ratings). Then, we created the fictitious account for each subject at Amazon.com and entered their product ratings—the first 5 or 15 ratings depending on the treatment condition to which the subject was assigned. 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 knowledge. Then, they logged on to their account at Amazon.com and picked two DVD items for themselves subject to a $50 budget constraint. Subjects did not have a time deadline and they could choose any DVD items that were available at Amazon. com. However, all of the subjects ended up picking movies they had seen before. Finally, subjects evaluated various aspects of the purchase experience including the quality of PPRs and indicated their repurchase intention. While the subjects were browsing at Amazon.com, we captured their clickstream data. To motivate subject involvement with the task, a lottery drawing was offered to all participants. There were a total of 20 first-prize winners, who won two DVDs they picked in the experiment, and 50 second-prize winners, who won one DVD.

Measurement

Appendix A lists all measurement scales and items. Following previous studies (e.g., Adler et al. 2002; Adomavicius and Tuzhilin 2002; Geoffrion and Krishnan 2001), the quality of PPRs was measured with consumers' perceptions about the extent to which the recommended items matched their preferences or fitted their taste. Theoretically, "quality of PPRs" and "perceived quality of PPRs" are two different concepts. Perceived quality of PPRs may not be an accurate measure of the quality of PPRs when consumers are not able to fully evaluate the quality of PPRs for reasons such as lack of product knowledge. This usually happens with products that are complex, such as houses, cars, computers, and cameras. In this study, the target product category is DVDs. Consumers should not experience difficulty in accurately evaluating the extent to which PPRs fit their taste for items they have watched or heard about before. It is true that PPRs sometimes include items consumers have never heard about, and in those instances, consumers' perceptions are not an accurate measure of the quality of PPRs. The challenge is that an objective way to evaluate the quality of PPRs for DVDs does not exist because only consumers can decide whether or not an item fits their taste. Therefore, "perceived quality of PPRs" is the only feasible measure of "quality of PPRs" in the context of this study.

Because no established scale could be found in the literature to measure consumer website knowledge, we used a self-developed scale to evaluate consumer website knowledge based on their subjective assessment of familiarity with Amazon.com's website. We adapted the scales developed by Chatterjee and Heath (1996) and Pereira (2001) to assess consumers' product evaluation cost and product screening cost separately. Online product brokering quality was measured by a scale for consumer decision-making confidence (Bearden et al. 2001; Pereira 2001; Tsiros and Mittal 2000), which is a consumers' subjective evaluation about their decision-making quality (Gul 1983). Xia (1999) points out that since the absolute "accuracy" of a consumer decision is difficult to measure and is quite often vague, and since the decision outcome is usually far in the future, decision-making confidence is a better indicator of decision-making quality from the consumers' perspective. Moreover, for the target product category we chose in the study, DVDs, only consumers can determine which items match their preferences. Therefore, in the context of this study, consumer decision-making confidence is arguably an adequate measure of consumer decision-making quality. Finally, the dependent variable, consumers' repurchase intention, was measured using a scale from previous studies (e.g., Jones et al. 2000; Mittal et al. 1998).

For control variables, we measured consumers' product knowledge as the total number of items they had watched out of 134 items on Amazon.com's top seller DVD list. We evaluated consumers' subjective evaluation of website usability using a three-item scale developed by Wolfinbarger and Gilly (2003.) The measure for product selection, assessing the variety available on the website, was operationalized as per the recommendations of Zeithaml et al. (1996.) The quality of product information was operationalized using the three-item scale from McKinney et al. (2002). A purchase involvement scale developed by Smith and Bristor (1994) was adapted to measure consumer decision-making involvement. Price perception was operationalized using the measure suggested by Bei and Chiao (2001). Finally, we collected various consumer demographics including age, gender, and Internet experience.

Results

Sample Description

We recruited a total of 366 business school undergraduate students in phase I. They all completed the movie rating part of the study, but only 273 appeared at the lab for phase II and finished the whole study. From that group, we dropped 16 students who rated fewer than 15 items. After all of the data collection was completed, we examined the subjects' click-stream data, and eliminated four students who did not log onto their own fictitious account as instructed. This process yielded a final sample size of 253, with 126 subjects in the high input group and 127 in the low input group. The sample is comprised of 43 percent females and 57 percent males with an average age of 21. They have between 3 and 10 years of experience with the Internet and the average is 7 years. Analysis of variance indicated that the subjects in the two groups were similar in profile based on age, years of Internet experience, and gender. Out of the 134 top seller DVDs, the total number of items watched ranges from 15 to 134 with an average of 36. Descriptive statistics for research constructs are presented in Table 1.

Measurement Scale Evaluation

Measurement scales were previously refined through three rounds of pilot studies. To evaluate the psychometric properties of all of the measurement scales in the main study, we first performed a factor analysis with varimax rotation using SPSS; the results are presented in Appendix B. In addition, to assess the convergent and discriminant validity of all the multi-item measurement scales, we created the inter-construct correlation matrix (see Appendix C). The values on the diagonal are the square root of the average variance extracted (AVE) of each construct. As can be seen, the AVE of each of 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 convergent and discriminant validity. Finally, we calculated the Cronbach coefficient alpha for each multi-item construct, all of which demonstrate very high internal consistency with alpha greater than .80 (see Table 2).

Manipulation Check

As a manipulation check, we conducted an ANOVA (Table 3) to compare the 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 our prediction. Subjects in the high input group perceive the quality of PPRs to be significantly higher than subjects in the low input group. Because the main purpose of using a manipulation was to generate sufficient variance in the quality of PPRs, we also checked its distribution. The results showed that there was no significant deviation from the normal distribution, which indicates that the goal of the manipulation has been achieved.

Table 1. Descriptive Statistics (n = 253)

Variable	Minimum	Maximum	Mean (Std. Dev.)
Quality of PPRs	1	7	4.38 (1.73)
Website Knowledge	1	7	4.11 (1.39)
Product Screening Cost	1	7	3.88 (1.32)
Product Evaluation Cost	2	7	2.98 (1.49)
Decision Making Quality	1.33	7	4.98 (1.27)
Repurchase Intention	1	7	4.58 (1.53)
Product Knowledge	15	134	36.01 (17.01)
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)
Decision-Making Involvement	1.33	7	4.93 (1.57)
Price Perception	1	7	4.80 (1.43)
Gender (1 = female)	0	1	.43 (.49)
Age	18	28	20.63 (1.50)
Internet Experience (years)	3	10	7.32 (1.79)

Table 2. Reliability of Measurement Scales (n = 253)

Construct	Cronbach's Alpha (Number of Items)
Quality of PPRs	.89 (3)
Website Knowledge	.85 (3)
Product Screening Cost	.93 (3)
Product Evaluation Cost	.88 (3)
Decision-Making Quality	.85 (3)
Repurchase Intention	.90 (3)
Website Usability	.92 (3)
Quality of Product Information	.94 (3)
Product Selection	.89 (3)
Decision-Making Involvement	.81 (3)
Price Perception	.89 (3)

Note: Product knowledge is a single item measure, therefore Cronbach alpha does not apply.

Table 3. ANOVA Result (Dependent Variable – Quality of PPRs) (n = 253)

Group	Number of Items	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 $\alpha = 0.001$

Hypothesis Tests

We performed preliminary analyses to examine the effect of the quality of PPRs on consumer online product brokering efficiency and store loyalty. Consistent with our predictions, results of ANOVAs (see Appendix F) showed that the high input group had a significantly lower product screening cost and higher product evaluation cost, decision-making quality, and repurchase intention than the low input group.

Next, we used PLS to estimate the structural model. Due to the small sample size and number of items in the measurement model, Lisrel was not appropriate for the model estimation. PLS has been widely applied to estimate structural equation models for small samples where the variables do not follow a multivariate-normal distribution (e.g., Agarwal and Karahanna 2000). The heuristic is that the sample size should be at least 10 times the largest number of structural paths directed at any one construct (e.g., Subramani 2004). In our model, the three mediating variables that measure consumer online product brokering efficiency (product screening cost, product evaluation cost, and decision-making quality) are the constructs with the largest number of paths coming in, which is seven, therefore, the minimal sample size to run this model using PLS is 70, and a sample size of 253 should be sufficient.

In a PLS structural model, the outer loading of each indicator on its corresponding construct is interpreted as a loading in a principal components factor analysis (Agarwal and Karahanna 2000). The PLS output shows that the outer loadings of all the indicators are above .7 and significant at .001 (see Appendix D). Estimation results for the model are presented in Figure 3. All path coefficients are also reported in Appendix E for the model with all paths and with significant paths only, and the results of hypotheses testing are summarized in Table 4.

Both exogenous variables in the model (the quality of PPRs and consumer website knowledge) exhibit a significant impact on consumer online product brokering efficiency. Consistent with our prediction, higher quality PPRs have a significant negative association with consumer product screening cost (H1a) and a positive association with consumer product evaluation cost (H1b) and consumer decision-making quality (H1c). Therefore, hypothesis H1a, H1b, and H1c are all supported. In addition, higher website knowledge is negatively associated with consumer product screening cost and positively associated with consumer decision-making quality, thus providing support for H2a and H2b.

We also find that consumer repurchase intention is negatively associated with consumer product screening cost and positively associated with consumer decision-making quality, however, consumer product evaluation cost does not show any significant impact on consumer repurchase intention. Therefore, H3a and H3c are supported, but H3b is not.

Some control variables were also found to be significant in the study. Website usability is positively related to decision-making quality. Product selection has a negative effect on product evaluation cost, and consumers' decision-making involvement has a positive relationship with product evaluation cost and decision-making quality. Finally, price perception is positively related to consumers' repurchase intention.

Tests for Bias and Robustness

We conducted a series of tests to ascertain the possibility of bias and establish the robustness of our findings. A potential threat to hypothesis testing using survey data is common method bias. We took several measures suggested by Podsakoff et al. (2003) in the design of the study to minimize this effect. First, in order to ensure temporal separation of measurement instruments, two important constructs (consumers' website knowledge and product knowledge) were measured before the subjects visited the website, while all other constructs were measured after the website visit. Moreover, the data were collected without identification of specific subjects, ensuring respondent anonymity. However, common method bias still could be a concern because many constructs in the model were measured at the same time, with a similar method, and rated by the same individual.

As recommended by Podsakoff et al., we first conducted the Harmon one-factor test, which requires that we load items used to measure all the constructs in the model into a single exploratory factor analysis. The analysis produced nine factors with eigenvalues greater than one and the first extracted factor accounted for 34 percent of the variance in the data. As more than one factor was extracted and less than 50 percent of the variance can be attributed to the first factor, the literature (e.g., Keil et al. 2007) suggests that common method bias is unlikely to be a significant issue with our data.

To further eliminate the threat of common method bias, following previous studies (e.g., Carlson and Kacmar 2000; Carlson and Perrewe 1999; Conger et al. 2000), we created a latent variable, the *method factor*, comprised of the indicators of all of the constructs in the model, and then we included the method factor as a predictor of all endogenous variables in the structural model: product evaluation cost, product screening cost, decision-making quality, and repurchase intention. Unlike Lisrel, PLS does not generate goodness of fit indexes

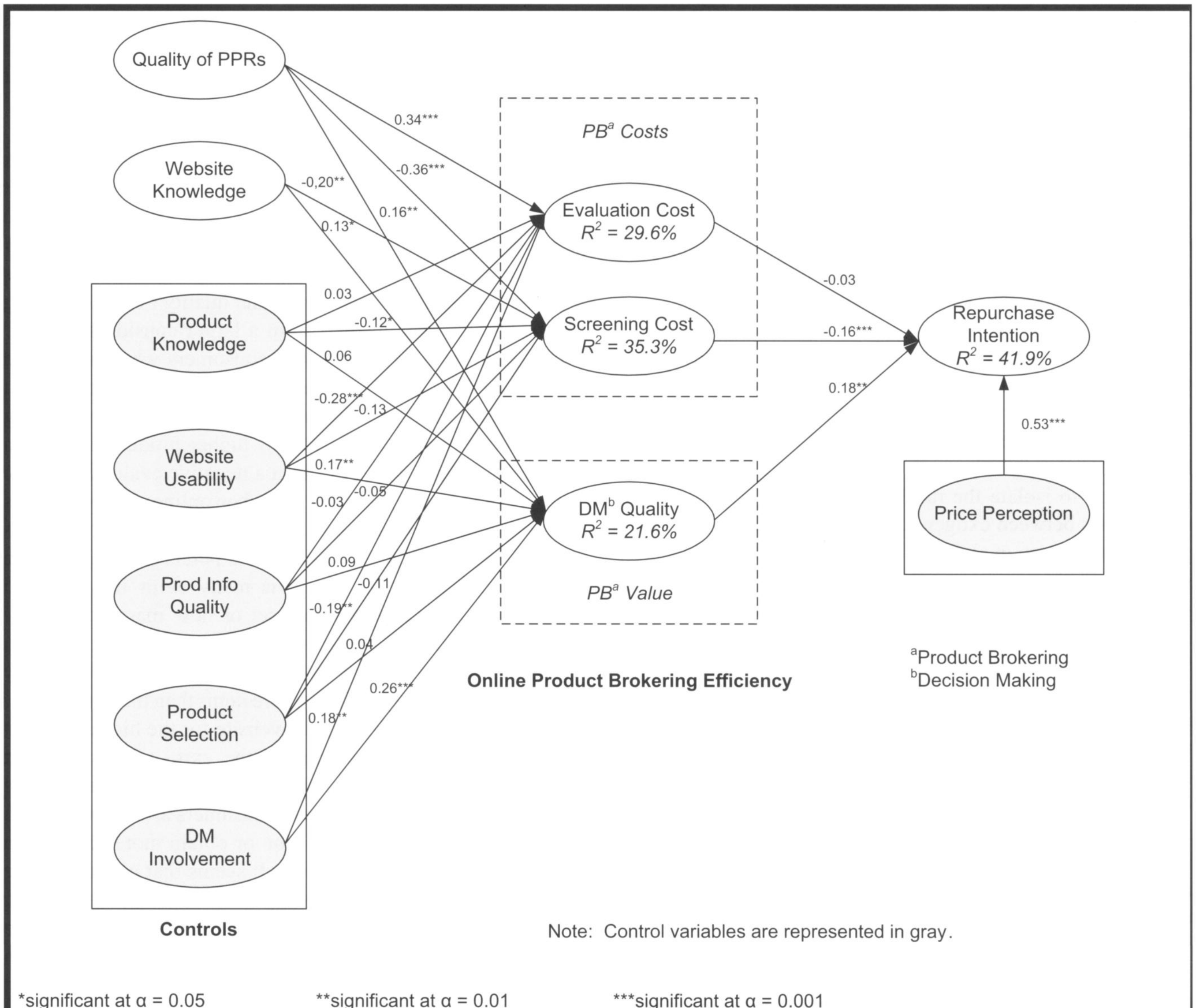

Figure 3. Results with PLS (n = 253)

Table 4. Hypotheses Testing Summary

	Hypotheses	Supported
H1a	Quality of PPRs → Product Screening Cost	✓
H1b	Quality of PPRs → Product Evaluation Cost	✓
H1c	Quality of PPRs → Decision-Making Quality	✓
H2a	Web Knowledge → Product Screening Cost	✓
H2b	Web Knowledge → Decision-Making Quality	✓
H3a	Product Screening Cost → Repurchase Intention	✓
H3b	Product Evaluation Cost → Repurchase Intention	n.s.
H3c	Decision Making Quality → Repurchase Intention	✓

for the model; therefore, for each endogenous variable, we conducted a pseudo f-test to check whether the improvement in R-square by adding the method factor was significant (Subramani 2004). Although the R-square for all the endogenous variables increased to different extents after the method factor was included, none of the pseudo f-tests was significant at $\alpha = 0.05$ level except repurchase intention. However, all of the significant paths in the original model retained their significance after controlling for this effect; therefore, we conclude that the coefficient estimates in the model are not biased due to common method variance.

Our conceptual development was grounded in the household production function model that argues for the mediating presence of online product brokering efficiency in the relationship between retailer and consumer learning and store loyalty. Mediating effects are important because they allow researchers to isolate the mechanisms underlying observed correlations between exogenous factors and dependent variables (MacKinnon et al. 2007). To further validate the existence of mediation, we estimated a model in PLS that included direct effects from retailer and consumer learning to store loyalty, in addition to the mediated effects. Results show that the mediating influence is robust and remains significant even after controlling for the direct effects. The direct effects in this model were also significant, indicating that the mediating variables are partial mediators. Similar results have been found in numerous previous studies (e.g., Carrillat et al. 2009; Cronin et al. 2000; Taylor et al. 1997) that tested the mediating effect of customer satisfaction between service quality and store loyalty, which has been adopted as the dominant framework in the literature to explain consumer store loyalty.

Discussion

The goal of this study was to address the following question: Do PPRs generate value for online retailers and, if so, how? Using the household production function model integrated with the human capital perspective as the theoretical foundation, we conceptualized and empirically tested the mechanism through which technological capabilities in the form of PPRs amplify the store loyalty of online consumers. Our findings provide strong support for the proposed model and explain significant variance in the dependent and mediating variables. We find, as expected, that by searching the whole database and screening all of the products on behalf of consumers, higher quality PPRs are associated with lower consumers' product screening cost and higher consumer decision-making quality, which in turn, is positively associated with consumer repurchase intention. With the extra resources saved from product screening, consumers are able and willing to form a larger consideration set and give in-depth evaluation of more items and, thus, higher quality PPRs result in higher consumer product evaluation cost.

Contrary to our prediction, the findings show that higher consumer product evaluation cost does not significantly affect consumer repurchase intention. There are two plausible explanations for this finding. First, the reason that higher quality PPRs increase consumer product evaluation cost is because consumers receiving higher quality PPRs are willing to inspect more items and form a larger consideration set. This phenomenon is similar to consumers who walk into a store and find there is a wide selection of items that may fit their needs. Although they may spend more time evaluating all of these items and thus incur higher product evaluation cost, this is unlikely to result in a negative evaluation of the store. This result may imply that when online shoppers assess their product brokering efficiency, product evaluation cost is not incorporated because consumers perceive this cost to be fully under their control. How many items they want to include in their consideration set or how many items they want to give serious consideration is completely the decision of individual consumers. Although higher quality PPRs may entice consumers to evaluate more items than they usually do, consumers will not blame the website for the higher product evaluation cost because that is the extra time and effort consumers are willing to spend. Moreover, at the price of higher product evaluation cost, consumers are able to reach a higher quality purchase decision or obtain more value from the product brokering process. It seems that consumers are able to distinguish the two types of cost incurred during online shopping, cost under the control of the online store (i.e., product screening cost) and the cost under their own control (i.e., product evaluation cost). The latter type of cost does not affect consumers' attitudes toward the online store and repurchase intentions.

In general, we believe that higher quality PPRs amplify consumers' repurchase intention by reducing consumer product screening cost and improving consumer decision-making quality. Although consumer product evaluation cost will go up with higher quality PPRs, it does not affect consumers' repurchase intention because consumers have complete control over how many items they evaluate. If they feel that there are too many items recommended by the online store, they can stop at any time.

It is important to note that in addition to PPRs, many other aspects of retailer services such as website usability, product selection, and product information quality can also significantly affect consumer online product brokering efficiency.

Our findings, however, show that the quality of PPRs remains a significant determinant of consumer online product brokering efficiency after controlling for the effects of these other variables. Moreover, price perception also demonstrates a very strong impact on consumer repurchase intention. This finding is not surprising given that all of the subjects in the experiment are college students, a group of highly price conscious consumers. After controlling for price perception, product screening cost and decision-making quality are still significant, suggesting that consumer online product brokering efficiency is an important driver of consumer store loyalty.

Limitations

Prior to discussing the implications of the findings, we acknowledge the limitations of this study. First, an assumption underlying our conceptualization is that consumers engage in some amount of product brokering after 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, especially when the consumer visits an online store with a specific and well-defined purchase need where the product has already been selected. Second, this study focuses on a single product category: DVDs. The findings may not be generalizable to other product categories. Third, decision-making confidence was used in the study to measure consumer decision-making quality. Decision-making confidence collected at the moment of purchase can be an accurate measure of consumer decision-making quality when consumers select DVD items they have watched before, which is the case in the study. However, when consumers choose DVD items they have not watched before, to accurately measure consumer decision-making quality, a longitudinal study should be used to assess decision-making confidence after product consumption (i.e., after consumers have watched the DVD items).

Fourth, the experimental setting was Amazon.com, a reliable and trusted electronic merchant. These results might not hold for less well-known and trusted retailers. Fifth, the data was collected from a simulated purchase in a lab setting. Although a lottery drawing was offered to all of the subjects to improve their decision-making involvement, consumers may behave differently for a real purchase in a natural setting. Sixth, in the experiment, the subjects did not go through the entire shopping process and skipped some stages, such as checking out the products, having the products delivered to their home, and returning the products if something was wrong. Online retailers' services in these stages, such as shipping charges, shipping options, order tracking, and on-time delivery, may also affect consumers' shopping efficiency and repurchase intention (Gauri et al. 2008). A retrospective survey or a longitudinal study could be used in the future to investigate the impact of other retailers' services on consumers' store loyalty. Finally, we used a single website, Amazon.com, in this study to control all of the features of recommender systems while generating sufficient variance for the core variable, the quality of PPRs. Although this strategy allowed us to control for other confounding factors, the results may not be generalizable to other websites.

Implications for Research

As one of the first empirical studies to investigate whether and how PPRs are associated with customer store loyalty online, our findings have important implications for researchers. First, in the literature on services marketing, the dominant theoretical framework to study customer store loyalty is the service quality—customer satisfaction—customer store loyalty paradigm. 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). However, previous studies have pointed out several limitations with this model and called for alternative frameworks to better understand customer loyalty (e.g., Anderson et al. 1994; Anderson and Sullivan 1993; Jones and Sasser 1995; Neal 1999; Oliver 1999; Reichheld 1996). Although the household production function model has been used to understand why consumers prefer certain consumption activities over others (e.g., Becker et al. 1994; Becker and Murphy 1988; Ratchford 2001; Stigler and Becker 1977), this is the first study that has applied this framework to explain customer store loyalty. Empirical results show that consumers' online product brokering efficiency in the form of product screening cost and decision-making quality are significantly associated with their store loyalty.

This study provides a rich theoretical framework to explain the mechanism through which higher quality PPRs influence customer store loyalty. Although we focused on PPRs, one form of personalized services, the conceptual framework developed in this study can be used to understand the impact of other personalized services on customer store loyalty in general. Consumers go through multiple stages to complete a purchase task and the different types of personalized services may influence consumer shopping efficiency at different stages. For example, just as PPRs affect consumer online product brokering efficiency, personalized promotion e-mails and a one-click ordering system may affect consumers' need recognition efficiency and purchase efficiency respectively. Future research can apply this framework to investigate how any specific personalized service or all personalized services offered by a retailer as a package influence consumer shopping efficiency and store loyalty.

Third, to the degree that online shopping requires a significant amount of cognitive effort, our findings show that learning by both consumers and retailers plays a key role in consumers' online shopping efficiency and store loyalty. 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 early empirical evidence that consumer learning, via its effects on the "value" component of product brokering efficiency can lead to cognitive lock-in, that is, consumers choose to stay with the current service provider to maximize their shopping efficiency. Surprisingly, compared to consumer learning, retailer learning has been overlooked in the literature. By personalizing their online shopping experience, effective retailer learning can improve customers' shopping efficiency and therefore improve customer store loyalty. When consumers switch to another store, their shopping efficiency will suffer. The longer they have stayed with the current store, the more difficult it is for them for them to switch.

In order to create a natural setting for the subjects while at the same time manipulating the core variable of this study—the quality of PPRs—we collected the data through a creatively designed lab experiment where we were able to control Amazon.com's recommender system such that it generated PPRs with various levels of quality. As pointed out by Kumar and Benbasat (2001), empirical research on 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.

Another theoretical implication for future research is to expand the model proposed here to include additional variables. Prior research has found variables such as consumer trust, perceived risk, and privacy concerns to be related to online shopping behaviors (Chellappa and Sin 2005; Gefen et al. 2003; Pavlou and Gefen 2005). The use of a single website in this study reduced the variance in these variables. Studies that incorporate multiple websites and their PPRs could consider measuring these variables more directly to isolate the precise effects of PPRs on repurchase intentions.

Finally, most previous research on recommender system design has focused on technical issues that could help improve the quality of PPRs. Findings of this study suggest that improving the quality of PPRs requires cooperation from consumers and it is not just a technical issue that can be solely solved by designers of recommender systems. Keeping everything else constant, the more input consumers provide to the recommender system, the higher the quality of PPRs they will receive. However, lack of sufficient input from individual consumers has significantly affected the quality of PPRs. 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 followed by empirical studies are needed to explore this issue.

Several important issues about PPRs remain to be investigated. First, do PPRs have a negative impact on consumer online product brokering efficiency and store loyalty when they are completely irrelevant, and, if so, what is the magnitude of this impact? Second, do PPRs increase consumers' likelihood of making an unplanned purchase? Third, this study did not distinguish two types of online shoppers: experiential versus 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. Finally, as we noted before, online retailers have an opportunity to use IT to offer a wide range of personalized services that may influence consumers' shopping efficiency at different stages. Theoretical frameworks and empirical analyses are needed for us to understand how personalization as a strategic package influences consumer shopping behavior in electronic markets.

Implications for Practice

From the perspective of practice, several implications follow from the findings. First, our results indicate 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 the consumers' online product brokering efficiency, the higher decision-making quality and the lower the product screening cost, and, finally, the higher consumers' repurchase intentions. This "virtuous cycle" offers significant value to retailers. Unlike other services offered by an online firm, theoretically, PPRs have the potential to bring sustained competitive advantage to online vendors as it becomes more and more difficult for competitors to imitate them. It takes time and cognitive effort for consumers to teach an online store about their preferences and taste in exchange for a more efficient shopping experience. When consumers switch to another store, their shopping efficiency will suffer, or they have to start over again and expend a significant amount of effort to teach the new store's recommender system their preferences in order to achieve the same level of shopping efficiency.

A report released by Jupiter Research (2003) suggests that PPRs are not appreciated by many online shoppers and their impact on consumer store loyalty is limited. According to the survey, poor quality is the primary 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, arguably lack of sufficient input from individual consumers is an important proximal cause of poor quality. Without adequate consumer knowledge, such as in the case of new or infrequent customers, it is very difficult for recommender systems to generate recommendations that closely match an individual consumer's preference.

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 the data are noisy. In contrast, although product ratings have a higher quality and can be collected quickly, entering product ratings demands a significant amount of time and cognitive effort from consumers. Without sufficient input, PPRs generated by the recommender system will have poor quality and will be perceived as useless by consumers, which will further reduce consumers' motivation to provide product ratings, thereby putting a vicious cycle into motion. To persuade consumers to make the initial investment, incentives may be necessary at the beginning. For instance, a store might offer a consumer a discount when purchasing DVDs if she rates a certain number of items. In addition, the interface of the recommender systems should be constantly improved to reduce the cost incurred by consumers when submitting product ratings.

An important finding of this study for online retailers is that it may be possible to lock in their customers through consumer learning. Results show that consumers' familiarity with an online store's website interface significantly improves their online product brokering efficiency by reducing their information search cost and increasing their decision-making quality. Online firms seeking to lock in their customers should maintain a consistent website layout and avoid any major changes. It should be noted that the lock-in through consumer learning cannot bring sustained competitive advantage to online firms because it is easy for rivals to imitate. Firms seeking to acquire new customers can change their website to make it look similar to those well-known and successful websites 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.

Retailers also need to understand that although personalization is a powerful tool to establish and maintain strong customer store loyalty, other aspects of services should not be neglected. A user-friendly website interface, a wide selection of products, high-quality product information, and reasonable prices are also attractive to online shoppers. Offering high-quality basic services is necessary, but not sufficient, for an online store to attract and retain customers. When a website fails to do this, customers will not come back no matter how sophisticated 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 best return.

Conclusion

Although one of the most important motivations for online firms to offer PPRs is an improvement in customer retention, empirical evidence on retention through PPRs is sparse, and the limited anecdotal evidence is contradictory. Building upon the household production function model in the consumer economics literature juxtaposed with the human capital framework, this study developed a theoretical framework that elaborates the mechanism through which PPRs influence customer store loyalty in the online shopping environment. Empirical analyses reveal that higher levels of consumer input to the recommender system are positively associated with the quality of PPRs, which in turn is positively associated with consumers' online product brokering efficiency: higher decision-making cost and lower product screening cost, and ultimately repurchase intention. An interesting finding of this study is that higher quality PPRs may increase consumer product evaluation cost incurred during the online product brokering process. At the expense of higher product evaluation cost, consumers are able to make a higher quality purchase decision and, thus, obtain more value from the online product brokering process. At the same time, the results of this study also reveal that the quality of basic services such as website usability, product selection, quality of product information, and price levels also have a significant impact on customer store loyalty and should not be ignored by online retailers. These insights 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 improve customer retention.

References

Adler, M., Gibbon, P., and Matias, Y. 2002. "Scheduling Space Sharing for Internet Advertising," *Journal of Scheduling* (5:2), pp. 103-119.

Adomavicius, G., and Tuzhilin, A. 2002. "Personalization Technologies in E-Business: Survey and Opportunities for OR Research," Working Paper, New York University.

Agarwal, R., and Karahanna, E. 2000. "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs about Information Technology Usage," *MIS Quarterly* (24:4), pp. 665-694.

Alba, J. W., and Hutchinson, J. W. 1987. "Dimensions of Consumer Expertise," *Journal of Consumer Research* (13), pp. 411-454.

Alba, J. W., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., and Wood, S. 1997. "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing* (61:3), pp. 38-53.

Anderson, E. W., Fornell, C., and Lehmann, D. R. 1994. "Customer Satisfaction, Market Share, and Profitability: Findings from Sweden," *Journal of Marketing* (58:3), pp. 53-66.

Anderson, E. W., and Sullivan, M. W. 1993. "The Antecedents and Consequences of Customer Satisfaction for Firms," *Marketing Science* (12:2), pp. 125-143.

Ariely, D., Lynch, J. G., and Aparicio IV, M. 2004. "Learning by Collaborative and Individual-Based Recommendation Agents," *Journal of Consumer Psychology* (14:1/2), pp. 81-95.

Bakos, J. Y. 1997. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science* (43:12), pp. 1676-1692.

Beach, L. R. 1993. "Broadening the Definition of Decision Making: The Role of Prechoice Screening of Options," *Psychology Science* (4:4), pp. 215-220.

Bearden, W. O., Hardesty, D. M., and Rose,R. L. 2001. "Consumer Self-Confidence: Refinements in Conceptualization and Measurement," *Journal of Consumer Research* (28:1), pp. 121-134.

Beatty, S. E., and Smith, S. M. 1987. "External Search Effort: An Investigation Across Several Product Categories," *Journal of Consumer Research* (14), pp. 83-93.

Becker, G., Grossman, M., and Murphy, K. M. 1994. "An Empirical Analysis of Cigarette Addiction," *American Economic Review* (84), pp. 396-418.

Becker, G., and Murphy, K. M. 1988. "A Theory of Rational Addiction," *Journal of Political Economy* (96), pp. 675-700.

Bei, L., and Chiao, Y. 2001. "An Integrated Model for the Effects of Perceived Product, Perceived Service Quality, and Perceived Price Fairness on Consumer Satisfaction and Loyalty," *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior* (14), pp. 125-140.

Bower, G. H., and Hilgard, E. R. 1981. *Theories of Learning*, Englewood Cliffs, NJ: Prentice-Hall.

Brynjolfsson, E and Smith, M. 2000. "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science* (46:4), pp. 563-585.

Carlson, D. S., and Kacmar, K. M. 2000. "Work–Family Conflict in the Organization: Do Life Role Values Make a Difference?," *Journal of Management* (26:5), pp. 1031-1054.

Carlson, D. S., and Perrewe, P. L. 1999. "The Role of Social Support in the Stressor-Strain Relationship: An Examination of Work–Family Conflict," *Journal of Management* (25:4), pp. 513-540.

Carrillat, F. A., Jaramillo, F., and Mulki, J. P. 2009. "Examining the Impact of Service Quality: A Meta-Analysis of Empirical Evidence," *Journal of Marketing Theory and Practice* (17:2), pp. 95-110.

Census Bureau. 2008. http://www.census.gov.

Chatterjee, S., and Heath, T. B. 1996. "Conflict and Loss Aversion in Multiattribute Choice: The Effects of Trade-Off Size and Reference Dependence on Decision Difficulty," *Organizational Behavior and Human Decision Processes* (67:2), pp. 144-155.

Chellappa, R. K., and Sin, R. 2005. "Personalization Versus Privacy: An Empirical Examination of the Online Consumer's Dilemma," *Information Technology and Management* (6:2-3), pp. 181-202.

Chen, Z., and Dubinsky, A. J. 2003. "A Conceptual Model of Perceived Customer Value in E-commerce: A Preliminary Investigation," *Psychology & Marketing* (20:4), pp. 323-348.

Cho, N., and Park, S. 2001. "Development of Electronic Commerce User–Consumer Satisfaction Index (ECUSI) for Internet Shopping," *Industrial Management + Data Systems* (101:8/9), pp. 400-405.

Conger, J. A., Kanungo, R. N., and Menon, S. T. 2000. "Charismatic Leadership and Follower Effects," *Journal of Organizational Behavior* (21:70, pp. 747-767.

Cronin Jr., J. J., Brady, M. K., and Huit, G. T. M. 2000. "Assessing the Effects of Quality, Value, and Customer Satisfaction on Consumer Behavioral Intentions in Service Environments," *Journal of Retailing* (76:2), pp. 193-218.

Cronin Jr., J. J., and Taylor, S. A. 1992. "Measuring Service Quality: A Reexamination and Extension," *Journal of Marketing* (56:3), pp. 55-68.

Diehl, K., Kornish, L. J., and Lynch, J. G. 2003. "Smart Agents: When Lower Search Costs for Quality Information Increases Price Sensitivity," *Journal of Consumer Research* (30), pp. 56-71.

Einhorn, H. J., and Hogarth, R. M. (Eds.). 1987. *Decision Making Under Ambiguity*, Chicago: IL: University of Chicago Press.

Gauri, D. K., Bhatnagar, A., and Rao, R. 2008. "Role of Word of Mouth in Online Store Loyalty," *Communications of the ACM* (51:3), pp. 89-91.

Gefen, D., Karahanna, E., and Straub, D. W. 2003. "Trust and TAM in Online Shopping: An Integrated Model," *MIS Quarterly* (27:1), pp. 51-90.

Geoffrion, A. M., and Krishnan, R. 2001. "Prospects for Operations Research in the E-business Era," *Interfaces* (31:2), pp. 6-36.

Ghosh, A. 1994. *Retail Management* (2nd ed.), New York: The Dryden Press.

Gregan-Paxton, J., and John, D. R. 1997. "Consumer Learning by Analogy: A Model of Internal Knowledge Transfer," *Journal of Consumer Research* (24:3), pp. 266-284.

Griffith, D. A. 2005. "An Examination of the Influences of Store Layout in Online Retailing," *Journal of Business Research* (58), pp. 1391-1396.

Gul, F. A. 1983. " A Note on the Relationship between Age, Experience, Cognitive Styles and Accountants' Decision Confidence," *Accounting & Business Research* (15:53), pp. 85-88.

Haubl, G., and Trifts, V. 2000. "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science* (19:1), pp. 4-21.

Hitt, L. M., and Brynjolfsson, E. 1996. "Productivity, Business Profitability, and Consumer Surplus: Three Different Measures of Information Technology Value," *MIS Quarterly* (20:2), pp. 121-142.

Holyoak, K. J. (Ed.). 1984. *Analogical Thinking and Human Intelligence*, Hillsdale, NJ: Erlbaum.

Hostler, R. E., Yoon, V., and Guimaraes, T. 2005. "Assessing the Impact of Internet Agent on End Users' Performance," *Decision Support Systems* (41:1), pp. 313-323

Howard, J. A., and Sheth, J. N. 1969. *The Theory of Buyer Behavior*, Oxford, England: John Wiley & Sons.

Hoyer, W. D. 1984. "An Examination of Consumer Decision Making for a Common Repeat Purchase Product," *Journal of Consumer Research* (11:3), pp. 822-829.

Hutchinson, J. W., and Alba, J. W. 1991. "Ignoring Irrelevant Information: Situational Determinants of Consumer Learning," *Journal of Consumer Research* (18:3), pp. 325-345.

Jiang, P., and Rosenbloom, B. 2005. "Customer Intention to Return Online: Price Perception, Attribute-Level Performance, and Satisfaction Unfolding over Time," *European Journal of Marketing* (39:1/2), pp. 150-174.

Johnson, E. J., Bellman, S., and Lohse, G. L. 2003. "Cognitive Lock In and the Power Law of Practice," *Journal of Marketing* (67), pp. 62-75.

Jones, M. A., Mothersbaugh, D. L., and Beatty, S. E. 2000. "Switching Barriers and Repurchase Intentions in Services," *Journal of Retailing* (76:2), pp. 259-274.

Jones, T. O., and W. Sasser Jr., E. 1995. "Why Satisfied Customer Defect," *Harvard Business Review* (73:6), pp. 88-99.

Jupiter Research. 2003. "Jupiter Research Reports That Web Site 'Personalization' Does Not Always Provide Positive Results," Jupitermedia Corporation, Press Release, October 14 (http://www.jupitermedia.com/corporate/releases/03.10.14-newjupresearch.html).

Khalifa, M., and Liu, V. 2007. "Online Consumer Retention: Contingent Effects of Online Shopping Habit and Online Shopping Experience," *European Journal of Information Systems* (16:6), pp. 780-792.

Kahn, B. E., and McAlister, L. 1997. *Grocery Revolution: The New Focus on the Consumer*, Reading, MA: Addison-Wesley.

Keil, M., Depledge, G., and Rai, A. 2007. "Escalation: The Role of Problem Recognition and Cognitive Bias," *Decision Sciences* (38:3), pp. 391-421.

Kolesar, M. B., and Galbraith, R. W. 2000. "A Service-Marketing Perspective on E-tailing: Implications for E-retailers and Directions for Further Research," *Internet Research* (10:5), pp. 424-438.

Kumar, N., and Benbasat, I. 2001. "Shopping as Experience and Website as a Social Actor: Web Interface Design and Para-social Presence," in *Proceedings of the 22nd International Conference on Information Systems*, V. Storey, S. Sarkar, and J. I. DeGross (eds.), New Orleans, Louisiana, December 16-19, pp. 449-454.

Kumar, N., and Benbasat, I. 2006. "The Influence of Recommendations and Consumer Reviews on Evaluations of Websites," *Information Systems Research* (17:4), pp. 425-439.

Latcovich, S. and Smith, H. 2001. "Pricing, Sunk Costs, and Market Structure Online: Evidence from Book Retailing," *Oxford Review of Economic Policy* (17:2), pp. 217-234.

Liu, C., and Arnett, K. P. 2000. "Exploring the Factors Associated with Web Site Success in the Context of Electronic Commerce," *Information & Management* (38:1), pp. 23-33.

MacKinnon, D., Fairchild, A., and Fritz, M. 2007. "Mediation Analysis," *Annual Review of Psychology* (58), pp. 593-614.

Mason, B. J., Mayer, M. L., and Ezell, H. F. 1991. *Retailing* (4th ed.), Homewood, IL: Richard D. Irwin.

McKinney, V., Yoon, K., and Zahedi, F. 2002. "The Measurement of Web–Customer Satisfaction: An Expectation and Disconfirmation Approach," *Information Systems Research* (13:3), pp. 296-316.

Meister, F., Shin, D., and Andrews, L. 2002. "'Getting to Know You': What's New in Personalization Technologies," E-Doc, March-April (http://www.aiim.org/Resources/Archive/Magazine/2002-Mar-Apr/25187).

Melville, N., Kraemer, K., and Gurbaxani, V. 2004. "*Review*: Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (38:2), pp. 283-322.

Mittal, V., Ross Jr., W. T., and Baldasare, P. M. 1998. "The Asymmetric Impact of Negative and Positive Attribute-Level Performance on Overall Satisfaction and Repurchase Intentions," *Journal of Marketing* (62:1), pp. 33-47.

Moukas, A, Guttman, R., and Maes, P. 1998. "Agent-Mediated Electronic Commerce: An MIT Media Laboratory Perspective," in *Proceedings of the International Conference on Electronic Commerce*, Seoul, Korea, April 6-9.

Murthi, B. P. S., and Sarkar, S. 2003. "The Role of the Management Sciences in Research on Personalization," *Management Science* (49:10), pp. 1344-1362.

Neal, W. D. 1999. "Satisfaction Is Nice, But Value Drives Loyalty," *Marketing Research* (11:1), pp. 20-23.

Oliver, R. 1999. "Whence Consumer Loyalty," *Journal of Marketing* (63:Special Issue), pp. 33-44.

Park, C. W., Iyer, E. S., and Smith, D. C. 1989. "The Effects of Situational Factors on In-Store Grocery Shop," *Journal of Consumer Research* (15:4), pp. 422-433.

Pavlou, P. A., and Dimoka, A. 2006. "The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation," *Information Systems Research* (17:4), pp. (4), 391-412.

Pavlou, P. A., and Gefen, D. 2004. "Building Effective Online Marketplaces with Institution-Based Trust," *Information Systems Research* (15:1), pp. 37-59.

Pavlou, P. A., and Gefen, D. 2005. "Psychological Contract Violation in Online Marketplaces: Antecedents, Consequences, and Moderating Role," *Information Systems Research* (16:4), pp. 372-399.

Payne, J. W. 1976. "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior and Human Performance* (16), pp. 366-387.
Payne, J. W. 1982. "Contingent Decision Behavior," *Psychological Bulletin* (92), pp. 382-402.
Payne, J. W., Bettman, J. R., and Johnson, E. J. 1988. "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition* (14), pp. 534-552.
Pereira, R. E. 2001. "Influence of Query-Based Decision Aids on Consumer Decision Making in Electronic Commerce," *Information Resources Management Journal* (14:1), pp. 31-48.
Pierrakos, D., Paliouras, G., Papatheodorou, C., and Spyropoulos, C. D. 2003. "Web Usage Mining as a Tool for Personalization: A Survey," *User Modeling and User-Adapted Interaction* (13:4), pp. 311-372.
Podsakoff, P. M., MacKenzie, S. B., Lee, J-Y., and Podsakoff, N. P. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology* (88:5), pp. 879-903.
Ratchford, B. T. 2001. "The Economics of Consumer Knowledge," *Journal of Consumer Research* (27:4), pp. 397-411.
Ray, G., Muhanna, W. A., and Barney, J. B. 2005. "Information Technology and the Performance of the Customer Service Process: A Resource-Based Analysis," *MIS Quarterly* (29:4), pp. 625-652.
Reichheld, F. F. 1996. "Learning from Customer Defections," *Harvard Business Review* (74:2), pp. 56-67.
Russo, J. E., and Dosher, B. A. 1983. "Strategies for Multiattibute Binary Choice," *Journal of Experimental Psychology: Learning, Memory, and Cognition* (9), pp. 676-696.
Slama, M. E., and Tashchian, A. 1985. "Selected Socioeconomic and Demographic Characteristics Associated with Purchasing Involvement," *Journal of Marketing* (49:1), pp. 72-82.
Smith, J. B., and Bristor, J. M. 1994. "Uncertainty Orientation: Explaining Differences in Purchase Involvement and External Search," *Psychology & Marketing* (11:6), pp. 587-607.
Sternberg, R. J. 1986. "Inside Intelligence," *American Scientist* (74), pp. 137-143.
Stigler, G., and Becker, G. 1977. "De Gustibus Non Est Disputandum," *American Economic Review* (67), pp. 76-90.
Subramani, M. 2004. "How Do Suppliers Benefit from Information Technology Use in Supply Chain Relationships?," *MIS Quarterly* (28:1), pp. 45-73.
Tam, K. Y., and Ho, S. Y. 2003. "Web Personalization: Is it Effective?," *IT Professional Magazine* (5:5), pp. 53-57.
Taylor, S. A., and Baker, T. L. 1994. "An Assessment of the Relationship between Service Quality and Customer Satisfaction in the Formation of Consumers' Purchase Intentions," *Journal of Retailing* (72:1), pp. 163-178.
Taylor, S. A., Nicholson, J. D., Milan, J., and Martinez, R. V. 1997. "Assessing the Roles of Service Quality and Customer Satisfaction in the Formation of the Purchase Intentions of Mexican Consumers," *Journal of Marketing Theory and Practices* (5:1), pp. 78-90.
Tsiros, M., and Mittal, V. 2000. "Regret: A Model of its Antecedents and Consequences in Consumer Decision Making," *Journal of Consumer Research* (26:4), pp. 401-417.
Vrechopoulos, A. P., O'Keefe, R. M., Doukidis, G. I., and Siomkos,G. J. 2004. "Virtual Store Layout: An Experimental Comparison in the Context of Grocery Retail," *Journal of Retailing* (80), pp. 13-22.
Vrechopoulos, A. P., Papamichail, G., and Doukidis, G. I. 2002. "Identifying Patterns in Internet Retail Store Layouts," in *Financial Engineering, E-Commerce and Supply Chain*, P. Pardalos and V. Tsitsiringos (eds.), Dordrecht, The Netherlands: Kluwer Academic Publishers, pp. 231-246.
Walsh, J., and Godfrey, S. 2000. "The Internet: A New Era in Customer Service," *European Management Journal* (18:1), pp. 85-92.
Weisberg, R. W., and Alba, J. W. 1981. "An Examination of the Alleged Role of 'Fixation' in the Solution of Several 'Insight' Problems," *Journal of Experimental Psychology: General* (110), pp. 169-192.
Wolfinbarger, M., and Gilly, M. C. 2003. "eTailQ: Dimensionalizing, Measuring and Predicting eTail Quality," *Journal of Retailing* (79:3), pp. 183-198.
Xia, L. 1999. "Consumer Choice Strategies and Choice Confidence in the Electronic Environment," paper presented at the American Marketing Association's Summer Educator's Conference, San Francisco, CA.
Xiao, B., and Benbasat, I. 2007. "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact," *MIS Quarterly* (31:1), pp. 137-209.
Zeithaml, V. A., Berry, L. L., and Parasuraman, A. 1996. "The Behavioral Consequences of Service Quality," *Journal of Marketing* (60:2), pp. 31-46.
Zhu, K., and Kraemer, K. L. 2005. "Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry," *Information Systems Research* (16:1), pp. 61-84.

About the Authors

Tongxiao (Catherine) Zhang is a lecturer in the marketing area at the Gatton College of Business and Economics, University of Kentucky. She received a B.S. from Beijing Polytechnic University in China, an M.S. from Purdue University, and a Ph.D. from the University of Maryland. Her research focuses on the impact of information technologies on retailers' strategies and behavior in electronic markets.

Ritu Agarwal is a professor and the Robert H. Smith Dean's Chair of Information Systems at the Robert H. Smith School of Business, University of Maryland, College Park. She is also the founder and director of the Center for Health Information and Decision Systems at the Smith School. Ritu has published over 75 papers on information technology management topics in journals such as *Information Systems Research*, *MIS Quarterly*, *Management Science*, *Communications of the ACM*, *Journal of Management Information Systems*, *Decision Sciences, IEEE Transactions,* and *Decision Support Systems.* She has served as a senior editor for *MIS Quarterly* and *Information Systems Research*. Her current research is focused on the use of IT in healthcare settings, information privacy and security, social networks and their impacts, and consumer behavior in technology-mediated settings.

Henry C. Lucas, Jr., is the Robert H. Smith Professor of Information at the Robert H. Smith School of Business, University of Maryland. He received a B.S. from Yale University and an M.S. and Ph.D. from the Sloan School of Management, Massachusetts Institute of Technology. Professor Lucas' research interests include IT-enabled transformations, the impact of information technology on organizations, IT in organization design, electronic commerce, and the value of information technology. He is the author of a dozen books and more than 70 articles in professional periodicals on the impact of technology, information technology in organization design, the return on investments in technology, implementation of information technology, decision-making for technology, and information technology and corporate strategy. His most recent books include *Information Technology: Strategic Decision Making for Managers* (Wiley, 2005), *Beware the Winners Curse: Victories that Can Sink You and Your Company* (with G. Anandalingham, Oxford University Press, 2004), *Strategies for E-Commerce and the Internet,* MIT Press. 2002), *Information Technology and the Productivity Paradox: Assessing the Value of Investing in IT* (Oxford University Press, 1999), and *The T-Form Organization: Using Technology to Design Organizations for the 21st Century* (Jossey-Bass, 1996). He was the vice president of publications for the Association for Information Systems from 1995–1998 and editor-in-chief of the AIS electronic journals, *Communications of AIS* and *Journal of AIS*, from 1998–2002. He has served on the faculties of Stanford University and New York University, and has spent sabbaticals at the IBM Systems Research Institute in La Hulpe, Belgium, INSEAD in Fontainebleau, France, and Nanyang Technological University in Singapore.