Peng Huang, Nicholas H. Lurie, & Sabyasachi Mitra

Searching for Experience on the Web: An Empirical Examination of Consumer Behavior for Search and Experience Goods

By lowering the costs of gathering and sharing information and offering new ways to learn about products before purchase, the Internet reduces traditional distinctions between search and experience goods. At the same time, differences in the type of information sought for search and experience goods can precipitate differences in the process through which consumers gather information and make decisions online. A preliminary experiment shows that though there are significant differences in consumers' perceived ability to evaluate product quality before purchase between search and experience goods in traditional retail environments, these differences are blurred in online environments. An analysis of the online behavior of a representative sample of U.S. consumers shows that consumers spend similar amounts of time online gathering information for both search and experience goods, but there are important differences in the browsing and purchase behavior of consumers for these two types of goods. In particular, experience goods involve greater depth (time per page) and lower breadth (total number of pages) of search than search goods. In addition, free riding (purchasing from a retailer other than the primary source of product information) is less frequent for experience than for search goods. Finally, the presence of product reviews from other consumers and multimedia that enable consumers to interact with products before purchase has a greater effect on consumer search and purchase behavior for experience than for search goods.

Keywords: information search, browsing behavior, experience goods, multimedia, Internet

Traditional models based on the economics of information search assume that consumers search for information until the marginal cost of search equals its marginal benefit (Moorthy, Ratchford, and Talukdar 1997; Ratchford, Lee, and Talukdar 2003; Stigler 1961). Building on this idea, Nelson (1970, 1974) classifies products into search and experience goods according to consumers' ability to obtain product quality information before purchase. Nelson argues that consumers conduct minimal prepurchase information search for experience goods but perform extensive search for search goods. However, several authors (e.g., Alba et al. 1997; Klein 1998; Peterson, Balasubramanian, and Bronnenberg 1997) have suggested that because the Internet enables consumers to learn from the experiences of others and to gather product information that is often difficult to obtain in offline settings (Klein 1998; Lynch and Ariely 2000), it makes all attributes searchable and erases differences between search and experience goods.

Peng Huang is a doctoral student (e-mail: peng.huang@mgt.gatech.edu), Nicholas H. Lurie is Assistant Professor of Marketing (e-mail: lurie@gatech.edu), and Sabyasachi Mitra is Associate Professor of Information Technology (e-mail: saby.mitra@mgt.gatech.edu), College of Management, Georgia Institute of Technology. The authors thank ComScore Media Metrix Inc. for providing the data and Sridhar Balasubramanian, John Lynch, Deborah MacInnis, and Allen Weiss for their helpful comments and suggestions. Roland Rust served as guest editor for this article.

An alternative perspective on information search is provided by research on how consumers acquire and process information to make decisions (Bettman et al. 1993; Ha and Hoch 1989; Lurie 2004; Lynch and Ariely 2000; Shugan 1980). This research shows that different types of information are associated with different cognitive processes that affect the way information is acquired, the amount of information acquired, and the time spent processing each piece of information (Johnson, Bellman, and Lohse 2003; Johnson and Payne 1985; Payne, Bettman, and Johnson 1988). If consumers seek different information for search and experience goods, this perspective implies that online search and purchase behavior may be different for these two types of goods.

This article bridges these different perspectives. We argue that though the Internet serves as an important information source for both experience and search goods, the type of information that consumers seek, and therefore the way they search and make choices, is different for the two types of goods (Ha and Hoch 1989; Hoch and Deighton 1989; Hoch and Ha 1986; Weathers, Sharma, and Wood 2007). These differences affect the amount of time spent per page of information, the number of pages searched, the likelihood of free riding (purchasing from a vendor that is not the primary source of product information), and the relative importance of interactive mechanisms (e.g., consumer recommendations). These differences in consumer behavior have important implications for marketing practice.

ISSN: 0022-2429 (print), 1547-7185 (electronic)

We examine these issues in two stages. First, we conduct a preliminary experiment that compares consumer perceptions of their ability to obtain product quality information for search and experience goods in online versus traditional retail settings. Second, using data on actual browsing behavior collected by placing tracking software on the browsers of a representative sample of U.S. households, we compare online browsing and purchase behavior for search versus experience goods.

In support of the idea that the Web makes all attributes "searchable," we find that differences between search and experience goods, in terms of the perceived ability to assess product quality before purchase, are less in online shopping than in traditional retail settings. Correspondingly, in examining the browsing data, we find that consumers spend similar amounts of time searching online for information on search and experience goods. However, we find significant differences in the way consumers search and purchase these two types of products online. In particular, experience goods involve greater depth of search (characterized by more time spent per product page), whereas search goods involve greater breadth of search (characterized by more product pages viewed). We also find that free riding (buying from a retailer other than the primary source of product information) occurs more frequently for search than for experience goods. Finally, we find that mechanisms used by Internet vendors to enable consumers to learn from the experience of others or experience product attributes before purchase (e.g., consumer feedback, third-party recommendations, multimedia presentations) increase the time spent on a Web site and the likelihood of purchase from that Web site to a greater extent for experience than for search goods.

We conclude from our empirical results that the search and experience goods classification (Nelson 1970, 1974) still provides important insights into consumer behavior in online environments. However, this is not because of differences in the ability to assess product quality before and after purchase, as originally conceptualized by Nelson (1970, 1974); rather, it is because of fundamental differences in the type of information consumers seek for these two types of products and, consequently, in their search and purchase behavior.

Although the experience versus search good classification has a long tradition in the marketing literature (Bloom and Pailin 1995; Ford, Smith, and Swasy 1990; Franke, Huhmann, and Mothersbaugh 2004; Wright and Lynch 1995) and despite the growing interest in online information search (Bucklin and Sismeiro 2003; Johnson et al. 2004; Klein and Ford 2003; Moe 2003; Moe and Fader 2004; Ratchford, Lee, and Talukdar 2003), this is the first study to examine differences in information search for the two product categories based on directly observed online consumer search behavior. The data set we examine enables us to observe information search directly and does not suffer from recall problems associated with self-reported data. In addition, following Winer (1999), we enhance the validity of our findings by combining experimental results with real-world data.

We organize the rest of the article as follows: The next section develops hypotheses that propose differences in consumer perceptions, online search patterns, and purchase behavior for the two types of products. The subsequent section describes the data and empirical analyses used to test our hypotheses. We then discuss the results, and in the final section, we offer conclusions and implications and discuss some limitations and possibilities for further research.

Consumer Information Search and the Internet

Assessing Product Quality

Nelson (1970, 1974) proposes a classification of search and experience goods based on consumers' ability to discover product quality before purchase. Although Nelson assumes that experience leads to certainty about product quality for experience goods, others argue that experience often provides ambiguous information, and thus consumers may remain uncertain about product quality even after gaining experience (Ha and Hoch 1989; Hoch and Deighton 1989; Hoch and Ha 1986). Notwithstanding extensions (Darby and Karni 1973) and qualifications (Alba et al. 1997; Hoch and Deighton 1989; Wright and Lynch 1995), the experience versus search good classification remains widely accepted in the marketing literature (Klein 1998).

Several researchers (e.g., Alba et al. 1997; Klein 1998; Peterson, Balasubramanian, and Bronnenberg 1997) have proposed that the Internet is likely to change the traditional relationship between search and experience goods. In particular, the Internet lowers the cost of gathering and sharing information (Hoffman and Novak 1996; Zettelmeyer, Morton, and Silva-Risso 2006) and offers new ways to learn about products before purchase (Lynch and Ariely 2000). For example, a well-designed Web site that sells premium wines can provide much richer information about the wine, such as its unique aromas and flavors, expert opinions, and consumer feedback, than wine labels in a traditional retail shop (Klein 1998). Similarly, consumers shopping for cameras can read extensive product reviews from other consumers and thus can "experience" these products before purchase.

An alternative perspective on the impact of the Internet on consumer search behavior is offered by decision-making researchers, who argue that information search involves both cognitive and physical effort (Johnson, Bellman, and Lohse 2003). For these researchers, the extent of information search, often measured by the number of acquisitions or the number of products viewed, occurs within, not just across, retailers and other providers of information (Diehl 2005; Häubl and Trifts 2000; Payne, Bettman, and Johnson 1988). This research stream also argues that different types of information (i.e., context variables) and different types of information structures (i.e., task variables) require different levels of effort to process, often measured by the "time per acquisition" (Bettman et al. 1993; Ha and Hoch 1989; Lurie 2004; Lynch and Ariely 2000; Shugan 1980). Other research has suggested that consumers change their decision strategies and, consequently, the cognitive costs of processing information as a function of effort versus accuracy trade-offs, product familiarity, and prior experience with a particular online retailer (Johnson, Bellman, and Lohse 2003; Johnson and Payne 1985; Payne, Bettman, and Johnson 1988).

Note that all products involve a bundle of search and experience attributes (Alba et al. 1997; Lynch and Ariely 2000). For the purpose of this research, we define search goods as those for which the attributes most important to assessing product quality are generally discoverable without the consumer (or someone else) interacting with the product; conversely, experience goods are those for which attributes associated with product quality are most discoverable through experience with the product. In our empirical analyses, to examine whether differences still exist in consumer behavior for search and experience goods, we use Nelson's (1970, 1974) original classification.

Depth Versus Breadth of Search

We define depth of search as the time a consumer spends evaluating information on a single Web page, and we define breadth of search as the number of product Web pages a consumer visits. Depth is similar to the time-per-acquisition variable, and breadth is similar to the number-of-acquisitions variable used in process-tracing research (Bettman et al. 1993; Bettman, Johnson, and Payne 1990; Lurie 2004), except that the unit of analysis is Web pages rather than attribute values. We argue that evaluating search and experience attributes involves different levels of effort and that the depth of search is likely to be greater (and breadth lower) for experience goods than for search goods. Search attributes (e.g., price) are objective, diagnostic, and easy to compare, whereas experience attributes (e.g., how easy a camera is to use) are inherently subjective, are characterized by uncertainty and equivocality, and are difficult to evaluate (Daft and Lengel 1984; Hoch and Deighton 1989; Hoch and Ha 1986). These differences can change the way consumers process information (Ha and Hoch 1989; Hoch and Ha 1986).

In particular, information about search attributes, such as price, color, shape, dimensions, and other standard product specifications, is typically presented in a straightforward manner and should require less time to obtain and process. In addition, comparisons across products are facilitated by the frequent presentation of this information in table or bullet format in online environments. Conversely, obtaining information about experience attributes may involve reading consumer ratings and feedback, inspecting products, evaluating videos or three-dimensional demonstrations of the product, downloading digital samples from the Web site, and referring to third-party product tests and recommendations (Hoch and Ha 1986; Weathers, Sharma, and Wood 2007). Furthermore, because information about experience attributes is likely to be highly idiosyncratic (e.g., the type of information provided about a product will vary because of individual differences in product experiences and the description of these experiences by particular reviewers), consumers must combine information from different sources to determine the overall value of a product alternative, evaluate attributes at a more abstract level, or restructure information to make it comparable (Coupey 1994; Johnson and Russo 1984; Johnson 1984, 1988). More generally, the increased uncertainty associated with experience attributes increases the amount of information consumers need to process and, therefore, the amount of time spent on each page of information (Ha and Hoch 1989). In line with information theory (Shannon and Weaver 1949), because each page of information on experience attributes reduces uncertainty to a greater extent, more information can be gathered in fewer pages, though the effort associated with processing this information should be higher (Garner 1962; Lurie 2004).

If the same number of product alternatives is displayed per Web page for both product types, we expect the following:

H_1: The number of product Web pages visited is greater for search goods than for experience goods.

H_2: The time spent examining a product Web page is longer for experience goods than for search goods.

The Free-Rider Problem

When promotional inputs, such as product consulting and retail showrooms, are not sold separately from the physical product, free-rider problems arise. In particular, online sellers can spend millions of dollars on Web sites that provide updated and extensive product information, and consumers can use these Web sites to decide which products to buy and then use shopbots or search engines to locate cheaper offerings (Chevalier and Mayzlin 2006). Recent evidence indicates that the Internet can exacerbate the free-rider problem (Carlton and Chevalier 2001; Morton, Zettelmeyer, and Jorge Silva-Risso 2001).

We argue that purchasers of experience goods are less likely than purchasers of search goods to engage in free-riding behavior. The basic intuition is that because greater effort is required to evaluate experience attributes (Hoch and Deighton 1989; Hoch and Ha 1986) and because information on experience attributes is likely to be presented through interfaces that are unique to each Web site (Johnson, Bellman, and Lohse 2003), the initial learning costs of using a particular Web site to acquire experience information will be higher. This should lead to "experience effects" that reduce incentives to learn new interfaces and increase cognitive lock-in (Johnson, Bellman, and Lohse 2003; Wood and Lynch 2002; Zauberman 2003), thus reducing free-riding behavior.

In addition, a major benefit of prepurchase search is to reduce the perceived risk associated with purchasing a product online (Ha 2002; Jacoby et al. 1994). In terms of search attributes, information provided by sellers reflects objective facts, and consumers have high confidence in the veracity of this information. Conversely, information about experience attributes is subjective and based on individual judgment and the heterogeneous tastes of consumers (Wright and Lynch 1995). With residual uncertainty for experience goods, a buyer is more inclined to buy experience goods from a trusted seller, and in many cases, this trusted seller will be the Web site that provides the buyer with the most extensive product information (Koch and Cebula 2002; Van Baal and Dach 2005). Thus, we propose the following:

H_3: Consumers of experience goods are more likely than consumers of search goods to purchase from retailers that are their primary information source.

Mechanisms for Communicating Experience Attributes

An important characteristic of the Internet as a retail channel is that it can enable a consumer to obtain information on experience attributes before purchase (Alba et al. 1997). Mechanisms through which Internet retailers can facilitate this transformation include consumer feedback, authoritative third-party information, and experience simulation (Klein 1998). Consumer feedback, through product reviews, online communities, and bulletin boards, provides a way to learn about the experience of others and is an important predictor of product adoption (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Mayzlin 2006). Authoritative third-party information, such as evaluations by *Consumer Reports*, also provides information on experience attributes (Ford, Smith, and Swasy 1988; Weathers, Sharma, and Wood 2007). Finally, experience simulation through multimedia content, such as travel sites that use three-dimensional demos, music vendors that provide sample downloads, camera retailers that offer high-definition sample photos, and virtual models that enable consumers to try on outfits, creates a direct experience for online shoppers (Lurie and Mason 2007; Schlosser 2003; Weathers, Sharma, and Wood 2007).

Although these three mechanisms likely increase the usage of a Web site (i.e., the time a consumer spends on a Web site searching for product information) as an information source, the effect of these mechanisms should be more pronounced for consumers searching for experience goods (West and Broniarczyk 1998). In particular, because information about search attributes can be effectively delivered in a simple manner, buyers of search products should be less willing to spend time viewing multimedia content or reading lengthy reviews. So, although search attributes can be conveyed through consumer feedback, third-party reviews, and experience simulation, it is easier to gather information on search attributes (e.g., price) through alternative means, such as shopbots. This suggests that consumers of experience goods are likely to spend more time at high-quality Web sites that implement the three mechanisms but that these mechanisms should have less effect on the behavior of consumers of search goods.

A related and important question for practitioners is whether these mechanisms actually increase the likelihood of purchase at a Web site and whether the effects differ across search and experience goods. Schlosser, White, and Lloyd (2006) argue that multimedia, along with other investments in Web design, serve as a signal of trustworthiness that increases purchase intentions. Schlosser (2003) shows that experience simulation through multimedia content increases purchase intentions for digital cameras (an experience good in Nelson's [1970, 1974] classification). We argue that these mechanisms increase purchase likelihood to a greater extent for experience than for search goods. In addition, we propose that there is a mediated relationship in this context for experience goods. The presence of experience transfer mechanisms increases the time consumers spend at Web sites for experience goods, and the resultant cognitive lock-in and reduced perceived risk make them more likely to buy from a Web site that implements such mechanisms:

H_4: The presence of (a) consumer feedback, (b) authoritative third-party information, and (c) experience simulation increases the time spent on a Web site to a greater extent for experience goods than for search goods.

H_5: The presence of (a) consumer feedback, (b) authoritative third-party information, and (c) experience simulation increases the likelihood of purchase at a Web site to a greater extent for experience goods than for search goods.

H_6: The positive effect of (a) consumer feedback, (b) authoritative third-party information, and (c) experience simulation on the likelihood of purchase for experience goods at a Web site is mediated by the time spent on the Web site.

Empirical Analysis and Results

To test our hypotheses, we performed the empirical analysis in two stages. First, we conducted a preliminary experiment to compare consumers' perceived ability to assess product quality before purchase for search versus experience goods in online versus offline environments. Second, we used data on consumers' browsing and purchase behavior to test H_1–H_6 by comparing browsing and purchase behavior for search versus experience goods. Although we draw on Nelson's (1970, 1974) product classification, note that all products involve a mix of search and experience attributes (Alba et al. 1997; Lynch and Ariely 2000). Thus, using a dichotomous classification lowers the likelihood of finding empirical differences, and our empirical tests are a conservative estimate of the actual differences.

Preliminary Experiment: Assessing Product Quality Before Purchase

The primary goal of our preliminary experiment was to demonstrate that differences in the perceived ability to evaluate product quality before purchase between products traditionally classified as search and experience goods are lower in online than in traditional retail environments. In the ComScore data (for which we provide more details subsequently) used to assess browsing and purchase behavior, products purchased by panelists are broadly classified into 60 different types. From these, we chose three search goods and three experience goods that matched with Nelson's (1970, 1974) original classification. We use Nelson's classification as a starting point because it is the original and most widely used classification of search and experience goods and because Nelson validated it using a variety of secondary data sets. We selected three types of search goods (Nelson 1970, p. 325)—shoes, home furniture, and garden and patio implements—and three types of experience goods (Nelson 1974, p. 738–39)—automotive parts and accessories, health and beauty products, and camera equipment. We selected these products for four reasons. First, they are among the few in the ComScore product classification scheme that exactly match those in Nelson's original classification of search and experience goods (see Nelson 1970, Table 2; Nelson 1974, Table 1). Second, they were frequently purchased during our study period, resulting in a reasonable sample size. Third, the product types represented a wide spectrum of price and product differentiation, from relatively inexpensive (shoes) to more expensive (cameras). Fourth, the products are not dominated by a few online sellers, which might limit consumers' prepurchase search.

Ninety undergraduate business students, who received class credit for participating, were randomly assigned to make assessments in either traditional retail or online purchase environments. In line with previous research (Hsieh, Chiu, and Chiang 2005; Krishnan and Hartline 2001), participants were told that the quality of some products and services is easy to assess before purchase but that other products and services cannot be easily assessed until after use. Participants in the traditional environment condition were asked to imagine that they were shopping at traditional retail stores for the products, and participants in the online environment condition were asked to imagine that they were shopping on the Internet. Participants were then asked to indicate their ability, before purchase, to access product quality for each of the six products on a seven-point scale ranging from "not at all" (1) to "very well" (7) and to indicate their ability, after using these products, to access the quality and performance of the same products on the same scale. We counterbalanced product order between subjects.

Preliminary Experiment Results

Means and standard deviations appear in Table 1. There was no significant effect of product order, so we combined the two order conditions. Overall, the results show that differences in the ability to assess product quality before purchase between search and experience goods are less for consumers shopping online than for consumers shopping in traditional retail settings. A repeated measures general linear model showed a significant interaction between product type (search versus experience) and shopping environment (traditional or online) in terms of the perceived ability to evaluate product quality before purchase ($F(1, 88) = 39.67$, $p < .001$). For consumers in the traditional offline shopping environment, the perceived ability before purchase to evaluate the quality of products Nelson (1974, 1970) classifies as search goods was significantly higher than that of products classified as experience goods ($M_{search} = 4.76$ versus $M_{experience} = 3.35$; $F(1, 88) = 56.07$, $p < .001$). However, for consumers shopping on the Internet, this difference was not significant ($M_{search} = 4.00$ versus $M_{experience} = 4.26$; $F(1, 88) = 2.01$, $p = .16$). Overall, the perceived ability to evaluate product quality before purchase was significantly higher for search than for experience goods ($M_{search} = 4.37$ versus $M_{experience} = 3.80$; $F(1, 88) = 18.42$, $p < .001$), but this main effect should be interpreted in light of the significant interaction between product type and shopping environment (online versus traditional retail). The main effect of shopping environment was not significant ($F(1, 88) = .20$, $p = .66$).

Comparison of the prepurchase means in Table 1 shows differences between search and experience goods in the traditional retail environment but not in the online environment. In particular, all search goods (shoes, home furniture, and garden and patio implements) scored higher than the scale midpoint of 4 ($t = 5.09$, $p < .001$), whereas all the experience goods (automotive parts and accessories, health and beauty, and camera equipment) scored lower than the scale midpoint ($t = –4.46$, $p < .001$). However, in the online environment, traditional search goods did not score higher than the scale midpoint ($t = –.06$, $p = .52$), whereas traditional experience goods did not score lower than the scale midpoint ($t = 1.48$, $p = .93$). Higher ratings for search goods (e.g., shoes, furniture) in the offline versus online environments may be driven by the ability to touch and feel these products before purchase in the offline environment. After-use means for all six products were significantly above the scale midpoint of 4 in both traditional retail and online environments ($t = 14.77$, $p < .001$, and $t = 21.44$, $p < .001$). Planned contrasts comparing prepurchase and after-use means for each of the six products in both traditional and online environments show that there was a significant increase in the perceived ability to assess product quality after use (all *p*s < .001), suggesting that none of these products are credence goods (Darby and Karni 1973).

The ComScore Data

To analyze consumer online search patterns, we used the ComScore 2004 disaggregate data set of Web site visitation and transaction activity. These data capture domain-level browsing and buying behavior of a representative sample of more than 50,000 households from all 50 United States and U.S. territories. Specifically, the data set captures every Web site (domain) visited by the consumer, the time stamp

TABLE 1
Perceived Ability to Assess Product Quality Before Purchase and After Use

		Search Goods			Experience Goods		
		Shoes	Furniture	Garden	Automotive	Health	Camera
Offline	Before purchase	4.87	5.07	4.33	3.33	2.87	3.84
		(1.62)	(1.25)	(1.40)	(1.48)	(1.27)	(1.48)
	After use	6.59	6.25	5.76	5.16	5.2	5.84
		(.73)	(.99)	(1.19)	(1.52)	(1.52)	(1.15)
Online	Before purchase	3.98	4.15	3.84	4.31	3.53	4.93
		(1.56)	(1.04)	(1.13)	(1.53)	(1.79)	(1.37)
	After use	6.42	6.04	5.71	5.58	6.04	6.16
		(.81)	(.85)	(1.06)	(1.37)	(1.19)	(.90)

Notes: Standard errors are in parentheses.

of the visit, the number of pages explored within the domain, and the total time spent on the domain during each browsing session. In addition, the data set contains the details of all transactions the consumer executed online—the specific product purchased, price paid, quantity, and vendor information, as well as household-level demographic data for each consumer. ComScore data from prior years have been used in recent research (Johnson et al. 2004; Moe 2003; Moe and Fader 2004).

We focused our attention on transactions that occurred in July 2004, providing a prepurchase period of six months, which we used to define the control variables employed in our empirical models, and avoiding the systematic differences in prepurchase search that may occur during the end-of-the-year holiday season. We identified 51 transactions for shoes, 28 for home furniture, 30 for garden and patio, 25 for automotive accessories, 53 for health and beauty products, and 23 for cameras during this period (after dropping observations for which demographic information was not available), which resulted in 210 transactions.

For each transaction in the six product categories, we collected transactional data on total price paid, the Web site on which the order was placed, and product quantity. Following previous research (Johnson et al. 2004), we define the 15 days preceding the purchase date as the prepurchase search period, such that multiple site visits associated with a single purchase are captured, but searches for different purchases are not inadvertently combined. In practice, we find that few panelists (<1%) made two or more purchases for products in the same category within a time span of 15 days, and we drop such data points from the analysis.

For each of the 210 purchase transactions in our data set, we manually examined all browsing sessions of the consumer in the prepurchase period to identify Web sites in each browsing session that either sell the specific product or provide relevant information about the product. We dropped sessions that were not associated with a transaction from the analysis. A limitation of the ComScore data set is that browsing-session data are at the domain level to protect consumer privacy, so detailed page-level statistics are unavailable. Therefore, if a buyer visits an online retailer that sells multiple types of products (e.g., Amazon.com), it is difficult to determine his or her specific search intention. To be conservative, we defined visits to such general Web sites as relevant to the current search only if the buyer's visit occurred within three hours of his or her visit to a specialized online seller of the product. In addition, to avoid counting sessions in which the buyer opens a browsing window and then leaves the session unattended, we discarded sessions for which the average page time of that session was greater than five minutes. To avoid counting pop-up advertisements, we excluded all browsing sessions that contained only a single Web page view. (The results are similar if the criterion for discarding pages is changed to six or seven minutes or if single page views are included in the analysis.) For the remaining domains, the search session data we collected included domain names, duration (in minutes) of the session, and the total number of pages the buyer viewed within the domain during the session. On average, each transaction involved browsing approximately three Web domains (for 666 observations). We tested H_1–H_3 at the transaction level (i.e., 210 observations) and H_4–H_6 at the domain level.

Dependent Variables

To assess search behavior, we used search time and number of pages viewed (rather than number of domains) because these measures more directly reflect consumers' opportunity costs of time and amount of information processed (Häubl and Trifts 2000; Moe 2003). Tot_time is the total time (in minutes) spent on search for a specific transaction in the 15 days before purchase and is calculated by summing the time spent on each product-related Web site visited by the consumer. Pages_viewed is the total number of product-related Web pages viewed for a given transaction in the 15 days before purchase, and Page_time is the average time per page (in minutes) spent on search for a given product in the 15 days before purchase. We defined a free rider as a buyer who obtains the majority of product information from (spends the most time on) one retailer's Web site but places his or her order elsewhere. For each transaction in our sample, we determined the retailer Web site at which the consumer spent the most time and coded the variable Free_rider as 0 for the transaction if this Web site matched the Web site from which the purchase took place and 1 if otherwise. In addition, Domain_time is the total time spent at a Web site by a consumer during the 15 days before purchase, and Purchase is an indicator variable defined for each Web site that is set to 1 if the purchase transaction occurred at that Web site and 0 if otherwise.

Independent Variables and Model

Exp_good is an indicator variable that is set to 1 for transactions that involved the purchase of an experience good and 0 otherwise. Because H_1–H_6 evaluate differences in search between experience and search goods, this variable is often the primary variable of interest in our models. In addition, for each Web site visited before a transaction, we manually determined which, if any, of the three experience transfer mechanisms were present on that Web site and coded this with three indicator variables—feedback, recom, and multimedia—that identified the presence of customer feedback, third-party recommendation, and experience simulation mechanisms, respectively.

Following previous research (Johnson et al. 2004; Moore and Lehmann 1980; Moorthy, Ratchford, and Talukdar 1997), we controlled for several variables that may affect consumer search, including total price paid; product familiarity, which was set to 1 if the consumer purchased any product in the same category during the six months before purchase and 0 if otherwise; and Internet shopping experience, defined as the total number of online purchases the consumer made during the prior six-month period. We also controlled for household income, highest education level for any member of the household, age of the eldest head of household, household size, and the presence of children. In addition, we created an indicator variable denoting Internet connection speed (dial-up = 0, and broadband = 1) and differentiated purely informational (nonselling) from retail Web sites using the indicator variable (seller).

To test the robustness of our results, we used standard and fixed-effect specifications, treating product category as a fixed effect nested within the search/experience categories for each of the dependent variables. Estimates from fixed-effects models are always consistent, even if the underlying effects are random (Cameron and Trivedi 2005; Wooldridge 2001). To evaluate H_1 and H_2, we estimated separate models for average page time and number of pages viewed. In addition, we examined whether there were significant differences in the total time spent on search. In Equation 1, dep_var is replaced by page_time, pages_viewed, and tot_time to create three separate models. We used log-transforms of dependent variables because the distributions of these variables are positively skewed (Greene 2003). We applied a similar transformation to the control variable tot_price:

$$
\begin{aligned}
(1)\quad \log(\text{dep\_var}) = {} & \beta_0 + \delta_1 \text{exp\_good} + \beta_1 \log(\text{tot\_price}) \\
& + \beta_2 \text{prod\_familarity} + \beta_3 \text{net\_shopping\_exp} \\
& + \beta_4 \text{income} + \beta_5 \text{education} + \beta_6 \text{oldest\_age} \\
& + \beta_7 \text{hh\_size} + \beta_8 \text{children} + \beta_9 \text{conn\_speed} + \varepsilon.
\end{aligned}
$$

Results

Descriptive statistics. Table 2 shows descriptive statistics of selected variables for each of the three search and three experience goods, and Table 3 shows descriptive statistics of the variables used to model browsing and purchase behavior.

Previous research based on the number of domains visited has documented limited search (e.g., Johnson et al. 2004), whereas we observe intensive online search effort in terms of total prepurchase search time. Although the average shopper visits an average of only 3.4 domains, he or she spends approximately 78 minutes and views 124 product pages for each online transaction (see Table 3). Even for products dominated by experience attributes (e.g., health and beauty products), buyers spend 47 minutes and view 61 Web pages before they make a final purchase (see Table 2). Consumer feedback was the most common experience transfer mechanism used in practice (36% of Web sites provided consumer feedback), whereas use of the other two experience transfer mechanisms was more limited in our sample.

Breadth of search. The coefficient of the exp_good variable has a significant and negative effect on number of pages searched (Table 4, Column A); we find similar results using a fixed-effects specification (Table 4, Column B), confirming H_1, which proposed that consumers of experience goods search fewer pages (M = 52.46 pages) than consumers of search goods (M = 79.04 pages; $F(1, 180) = 5.60$, $p < .05$). Furthermore, as do Johnson and colleagues (2004), we find that experienced Web shoppers tend to search more pages. Demographic variables were not significant predictors of the number of pages viewed.

Depth of search. In support of H_2 (Table 4, Column C), consumers of experience goods spend 19.5% more time per page (M = 54 seconds) than consumers of search goods (M = 44 seconds; $F(1, 180) = 4.89$, $p < .05$). We find similar results using a fixed-effects specification (Table 4, Column D). Consumers also spend less time per page as the total price of purchase decreases or as their shopping experience increases. Faster connection speeds reduce time per page by 19%. Other control variables are not significant, indicating that factors such as income, education, and age do not affect the time spent per page.

Total search time. Although we have no specific hypotheses for total search, we find that, contrary to traditional logic, which suggests that total search (time) should be much greater for search goods (Nelson 1970, 1974), there is no significant difference in the total amount of time spent searching for experience goods (M = 47 minutes) versus search goods (M = 58 minutes; $F(1, 180) = 1.77$, not significant [n.s.]; Table 4, Column E). We obtain similar results with a fixed-effects model. These results, along with those of the experiment, indicate that the Internet blurs the distinction between products traditionally classified as experience goods and those classified as search goods, though distinctions remain in search patterns between the two product categories. An increase in the number of Inter-

TABLE 2
Means (Medians) for Different Product Categories

Product Category	Number of Pages Viewed	Time per Page[a]	Total Time[a]	Percentage Free Riding	Average Price Paid	Number of Domains Searched
Search Goods						
Shoes	165.53(116)	.73 (.60)	93.47 (71)	16%	$50.55 ($39.99)	2.98 (2)
Home furniture	254.82 (54.5)	.91 (.87)	102.29 (49)	25%	$108.91 ($55.98)	4.76 (2)
Garden and patio	76.23 (39.5)	.95 (.74)	59.43 (33.5)	17%	$50.00 ($21.31)	2.73 (2)
Average	163.89 (82)	.84 (.70)	86.37 (53)	18%	$65.39 ($39.99)	3.51 (2)
Experience Goods						
Automotive parts and accessories	74.32 (46)	1.04 (1.10)	76.72 (47)	8%	$73.47 ($26.57)	4.43 (3)
Health and beauty	60.81 (42)	1.01 (.76)	46.60 (43)	9%	$60.94 ($45.96)	2.28 (2)
Cameras	133.61 (90)	.92 (.81)	107.91 (76)	4%	$320.24 ($331.65)	3.26 (2)
Average	80.73 (49)	.99 (.87)	68.02 (47)	8%	$123.09 ($49.95)	3.16 (2)

[a]Time per page and total time are in minutes.

TABLE 3
Dependent, Independent, and Control Variables

Variable	M	Mdn	SD	Minimum	Maximum
Dependent Measures					
Time per page[a]	.91	.76	.57	.04	3.42
Number of pages viewed	123.90	61	242.20	2	3075
Mean time in domain[a]	23.98	8	41.14	1	447
Number of domains searched	3.35	2	4.13	1	30
Total time[a]	77.54	50	77.63	2	449
Free rider (1 = yes)	.13	—	.34	0	1
Independent Variable					
Experience good (1 = experience good)	.48	—	.50	0	1
Control Variables					
Total price paid	$93.14	$47.50	$139.15	$0	$1,299.87
Product familiarity	.31	—	.46	0	1
Net shopping experience	23.22	10.50	33.19	0	203
Connection speed (1 = broadband)	.45		.50	0	1
Communication Mechanisms (1 if Present)					
Consumer feedback	.36	—	.48	0	1
Authoritative third-party recommendation	.06	—	.23	0	1
Experience simulation	.10	—	.30	0	1
Demographics[b]					
Education	2.80	2.50	1.35	0	5
Oldest age	6.91	7	2.44	1	11
Income	4.71	5	1.52	1	7
Children (1 if present)	.36	—	.48	0	1
Household size	2.84	2	1.33	1	6

[a]Time is in minutes.
[b]Education, oldest age, and income are demographic categorical variables coded into 6, 11, and 6 levels, respectively. Household size indicates the number of members in the household.

net purchases during the previous six months is associated with significant increases in the total time acquiring product information. It may be that these are hedonic shoppers who enjoy the online shopping process itself (Hoffman and Novak 1996).

The free-rider problem. To test H_3, which proposed that free riding is lower for experience goods, we estimated a logit model, in which $\Lambda(\cdot)$ is the inverse of logit function:

$$(2)\quad P(\text{freeride} = 1) = \Lambda[\beta_0 + \delta_1\text{exp\_good} + \beta_1\log(\text{tot\_price}) + \beta_2\text{prod\_familarity} + \beta_3\text{net\_shopping\_exp} + \beta_4\text{income} + \beta_5\text{education} + \beta_6\text{oldest\_age} + \beta_7\text{hh\_size} + \beta_8\text{children} + \beta_9\text{conn\_speed}].$$

The results show that the coefficient for the exp_good variable is significant and negative (Table 4, Column G), indicating that the probability of free riding is lower for buyers of experience than search goods ($z = -2.28$, $p < .05$). Correcting for the probability of purchasing from a given domain by chance alone (Malhotra 1982) led to a similar pattern of results for experience goods (19% free riding) versus search goods (44% free riding; $z = -4.04$, $p < .001$). We find similar effects using a fixed-effects specification (Table 4, Column H). We also find that free riding is (marginally) more common among heavy shoppers, as indicated by the coefficient for the net_shopping_exp variable in Columns G and H of Table 4. An increase in household income marginally lowers the likelihood of free riding. Other demographic variables were not significant.

Mechanisms for communicating experience attributes. H_4 proposed that online mechanisms that enable consumers to learn from the experiences of others, to read third-party reviews, and to virtually interact with products have a greater effect on the time spent on a Web site for experience goods than for search goods. We evaluate H_4 by aggregating search time by Web site (domain_time) for each transaction in our sample, which resulted in a sample size of 666 observations. Furthermore, for each Web site in the browsing history of a transaction, we manually determined whether any of the three experience transfer mechanisms (customer feedback, third-party recommendation, and experience simulation through multimedia) were present on that Web site through three indicator variables (feedback, recom, and multimedia, respectively). We also differentiate purely informational (nonselling) from retail Web sites using an indicator variable (seller). The three interaction terms (exp_good × feedback, exp_good × recom, and exp_good × multimedia) capture the differential impact of experience transfer mechanisms for search and experience goods. Furthermore, we include an additional interaction term (seller × exp_good) to capture the differential impact of the seller variable for search and experience goods. The resultant model is as follows:

TABLE 4
Differences in Search Behavior (Nelson's [1970, 1974] Original Classification)

	A: Number of Pages (H_1): Base Model[a]	B: Number of Pages (H_1): Fixed-Effect Model[b]	C: Time per Page (H_2): Base Model[a]	D: Time per Page (H_2): Fixed-Effect Model[b]	E: Total Search Time: Base Model[a]	F: Total Search Time: Fixed-Effect Model[b]	G: Free Riding (H_3): Base Model[c]	H: Free Riding (H_3): Fixed-Effect Model[d]
Experience good (Exp_good)	–.405** (.171)	–.365** (.176)	.195** (.088)	.197** (.091)	–.209 (.157)	–.168 (.161)	–1.206** (.548)	–1.443** (.578)
Total price paid (Tot_price)	.009 (.082)	.023 (.085)	.076* (.043)	.074* (.044)	.084 (.076)	.097 (.078)	.290 (.262)	.280 (.275)
Product familiarity (Prod_familiarity)	–.314 (.195)	–.297 (.208)	–.021 (.101)	–.012 (.108)	–.335* (.179)	–.309 (.191)	.023 (.579)	–.193 (.632)
Shopping experience (Net_shopping_exp)	.007** (.003)	.007** (.003)	–.002* (.001)	–.002* (.001)	.004* (.003)	.004* (.003)	.013* (.007)	.015** (.008)
Connection speed (Conn_speed)	.180 (.172)	.176 (.172)	–.189** (.089)	–.190** (.089)	–.009 (.158)	–.014 (.158)	–.683 (.534)	–.564 (.544)
Constant	3.413** (1.589)	3.293** (1.597)	.249 (.821)	.253 (.828)	3.662** (1.461)	3.546** (1.467)	–2.175 (1.704)	–2.577 (1.827)
Number of observations	209	209	209	209	209	209	209	209
R^2	.18	.19	.21	.21	.14	.15	.14[e]	.15[e]
Model fit	$F(28, 180) = 1.45$ ($p = .078$)	$F(30, 178) = 1.39$ ($p = .101$)	$F(28, 180) = 1.75$ ($p = .016$)	$F(30, 178) = 1.62$ ($p = .030$)	$F(28, 180) = 1.05$ ($p = .402$)[f]	$F(30, 178) = 1.03$ ($p = .436$)[f]	–2LL = 133.499 $\chi^2(28) = 31.138$ ($p = .311$)[f]	–2LL = 130.239 $\chi^2(30) = 34.398$ ($p = .265$)[f]

*$p < .10$.
**$p < .05$.
[a]Ordinary least squares model for Columns A, C, and E.
[b]Fixed-effect model for Columns B, D, and F.
[c]Binary logit model for Column G.
[d]Binary logit fixed-effect model for Column H.
[e]Cox and Snell pseudo-R^2 (logit model).
[f]We include a comprehensive set of covariates (education, oldest age, children, household size) for completeness. Many of these covariates are not significant. The children indicator is significant and negative in Columns E and F. The income categorical variables are significant in Columns G and H based on joint F-tests. Dropping education and oldest age makes the models for total search time significant. Dropping these covariates and adding the interaction between type of good (Exp_good) and price (thus controlling for differential slopes between these product types) makes the models for free riding significant.
Notes: Standard errors are in parentheses.

$$(3)\quad \log(\text{domain\_time}) = \beta_0 + \beta_1\text{seller} + \beta_2\text{exp\_good} + \beta_3\log(\text{tot\_price}) + \beta_4\text{feedback} + \beta_5\text{recom} + \beta_6\text{multimedia} + \beta_7\text{exp\_good} \times \text{feedback} + \beta_8\text{exp\_good} \times \text{recom} + \beta_9\text{exp\_good} \times \text{multimedia} \times \beta_{10}\text{exp\_good} \times \text{seller} + \varepsilon.$$

The results (Table 5, Column A) show that two of the three mechanisms that enable consumers to gain product experience before purchase (consumer feedback and experience simulation through multimedia content) significantly increase the amount of time spent in a given domain to a greater extent for experience goods. This is illustrated by the significant interaction of consumer feedback with experience good ($F(1, 655) = 5.71$, $p < .05$) and the significant interaction of experience simulation (multimedia) with experience good ($F(1, 655) = 6.25$, $p < .05$). For consumers of experience goods, the presence of consumer feedback increases time spent on a domain ($M = 2.19$ versus 1.51 minutes; $F(1, 655) = 16.49$, $p < .001$), as does experience simulation ($M = 2.19$ versus 1.51 minutes; $F(1, 655) = 7.80$, $p < .01$). We find similar results for a fixed-effects specification (Table 5, Column B). None of the experience transfer mechanisms had a significant main effect on time spent per domain for search goods. The presence of third-party recommendations did not have a significant impact on time spent in a domain. This provides support for H_{4a} and H_{4c} but not for H_{4b}.

H_5 proposed that the three experience transfer mechanisms have different impacts on purchase likelihood for search and experience goods. We used a logit version of Equation 4 to evaluate this hypothesis, in which the variable purchase is set to 1 if the purchase took place at the Web site and 0 if otherwise.

$$(4)\quad P(\text{purchase} = 1) = \Lambda[\beta_0 + \beta_2\text{exp\_good} + \beta_3\log(\text{tot\_price}) + \beta_4\text{feedback} + \beta_5\text{recom} + \beta_6\text{multimedia} + \beta_7\text{exp\_good} \times \text{feedback} + \beta_8\text{exp\_good} \times \text{recom} + \beta_9\text{exp\_good} \times \text{multimedia}].$$

Because purchase can take place only at a seller Web site, we dropped all nonseller, purely informational Web sites from the analysis. The results (Table 5, Column C) show that the presence of consumer feedback marginally increases the likelihood that the product will be purchased from that Web site for all goods (Wald $\chi^2(1) = 3.80$, $p < .10$) but more so for experience than for search goods, as indicated by the marginally positive interaction of exp_good with feedback (Wald $\chi^2(1) = 3.35$, $p < .10$). We find similar results using a fixed-effects specification (Table 5, Column D). In our data, third-party recommendations and experience simulation do not significantly affect purchase likelihood for either search or experience goods. Therefore, we find marginal support for H_{5a} but not for H_{5b} and H_{5c}.

H_6 proposed that for experience goods, time spent on a Web site mediates the relationship between the presence of experience transfer mechanisms and the likelihood of purchasing from that Web site. Figure 1 presents the direct and indirect effects of experience transfer mechanisms on purchase likelihood for experience goods. Among the three experience transfer mechanisms, a logit analysis shows that only the presence of consumer feedback significantly increases purchase likelihood (Wald $\chi^2(1) = 14.44$, $p < .01$). A mediation analysis shows that time per domain partially mediates the relationship between the presence of consumer feedback and purchase probability. When we use consumer feedback and domain time to predict purchase probability, domain time has a significant effect (Wald $\chi^2(1) = 46.78$, $p < .001$), while consumer feedback is marginally significant and the coefficient is smaller (Wald $\chi^2(1) = 3.24$, $p < .10$). A Sobel test confirms this mediation effect ($z = 3.53$, $p < .001$). Mediation cannot be claimed for third-party recommendation and multimedia mechanisms, because the direct effects of these variables on purchase probability are not significant. Therefore, the results provide support for H_{6a} but not for H_{6b} and H_{6c}.

Discussion and Conclusions

Summary and Theoretical Implications

This research investigates the differences in consumer search patterns between search and experience goods in the online context. By using data from actual consumers' browsing behavior, we can directly examine search patterns rather than rely on self-reported data. Overall, this article points to the continued relevance of the search/experience classification in online settings, but these distinctions are not based on consumers' perceived ability to access product quality before purchase; rather, as the differential effects of Web-based communication mechanisms illustrate, differences in the type of information sought precipitate distinct online browsing and purchase behavior.

As others have (Alba et al. 1997; Klein 1998), we argue that the Internet blurs distinctions between experience and search goods by providing mechanisms that enable online shoppers to gather information on experience and search attributes. Our experimental results support this proposition and suggest that the divide between search and experience goods, in terms of consumers' perceived ability to judge product quality before purchase, remains in traditional retail environments but erodes in the online environment. Our study of browsing behavior also supports this idea, in that the total time consumers spend online searching for product information is not significantly different for search and experience goods.

However, because evaluating experience attributes requires increased cognitive effort (Daft and Lengel 1984; Hoch and Deighton 1989; Hoch and Ha 1986), online consumer behavior for experience and search goods is distinct. In particular, we find that consumers view fewer pages but spend more time per page before purchasing experience

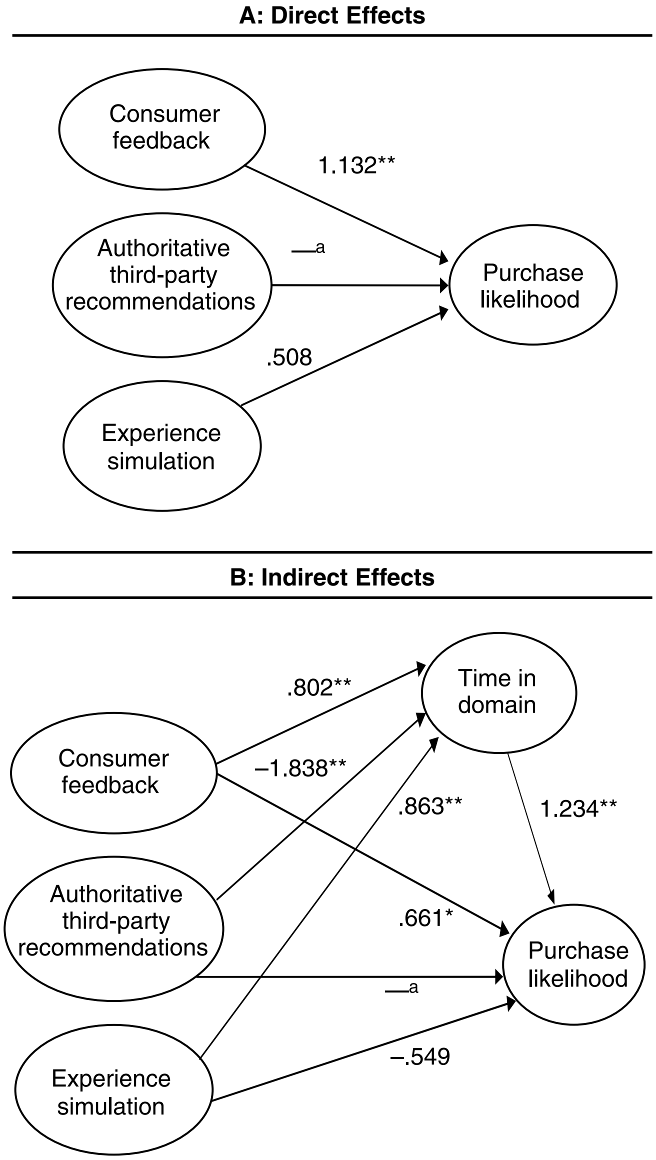
TABLE 5
Effect of Experience Transfer Mechanisms

	A: Domain Time (H_4)[a]	B: Domain Time (H_4): Fixed-Effect Model[a]	C: Purchase Likelihood (H_5)[b]	D: Purchase Likelihood (H_5): Fixed-Effect Model[b]
Constant	1.138***	1.133***	–.988***	–1.014***
	(.265)	(.266)	(.350)	(.351)
Web site type (1 = retailer)	1.015***	1.015***	—[c]	—[c]
(Seller)	(.156)	(.156)		
Total price	.067	.067	.021	–.015
Log(tot_price)	(.054)	(.057)	(.087)	(.090)
Experience good (1 = experience)	–.457**	–.460**	–.231	–.211
(Exp_good)	(.183)	(.184)	(.254)	(.256)
Exp_good × seller	.066	.065	—[c]	—[c]
	(.117)	(.117)		
Experience Transfer Mechanisms				
Consumer feedback (1 = present)	.128	.130	.481*	.489**
(Feedback)	(.161)	(.161)	(.246)	(.247)
Third-party recommendation	–.489	–.482	—[d]	—[d]
(Recom)	(.514)	(.516)		
Experience simulation	–.221	–.219	–.678	–.596
(Multimedia)	(.280)	(.283)	(.513)	(.517)
Exp_good × feedback	.555**	.559**	.669*	.660*
	(.233)	(.233)	(.365)	(.366)
Exp_good × recom	–.138	–.140	—[e]	—[e]
	(.572)	(.573)		
Exp_good × multimedia	.925**	.932**	.728	.599
	(.370)	(.375)	(.653)	(.661)
Number of observations	666	666	627[f]	627[f]
R^2	.154	.154	.083[g]	.086[g]
Model fit	$F(10, 655) = 11.93$	$F(12, 653) = 9.92$	–2LL = 767.487	–2LL = 765.414
	($p = .0000$)	($p = .0000$)	$\chi^2(6) = 27.90$	$\chi^2(8) = 29.97$
			($p = .0001$)	($p = .0002$)

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]Ordinary least squares model.
[b]Logistic regression.
[c]Dropped because purchase is not possible from a nonseller Web site. Thus, seller was a perfect failure predictor (when seller = 0) in logit for Columns C and D.
[d]Dropped because, in our sample, no transactions took place on Web sites that had third-party recommendations. Thus, recom was a perfect failure predictor (when recom = 1) in logit in Columns C and D.
[e]Dropped because of collinearity.
[f]39 cases in which either seller = 0 or recom = 1 was dropped, leading to a sample size of 627.
[g]Cox and Snell R-square.
Notes: Standard errors are in parentheses.

goods than search goods. In addition, we find that communication mechanisms, such as consumer feedback and experience simulation (e.g., consumer reviews, multimedia), increase the time spent in a domain but only for buyers of experience goods. Our finding that third-party opinions and recommendations do not significantly affect time per site may be due to the rarity of this mechanism in our sample or to lower consumer confidence in this retailer-controlled information (Friestad and Wright 1994; Mayzlin 2006). Further research could explore these issues and also examine the impact of other mechanisms, such as comparison charts and improved search functionality, on the time spent at a Web site and purchase probability for search and experience goods. We also discover that offering consumer

FIGURE 1
Mediation Analysis for Experience Goods (H_6)



*p < .10.
**p < .01.
[a]Dropped because, in our sample, no transactions took place on Web sites that had third-party recommendations (recom). Thus, recom was a perfect failure predictor for purchase likelihood in logit (when recom = 1).

feedback increases the likelihood that consumers will purchase from that seller, but this impact is greater for experience than for search products. Finally, we show that buyers of experience goods are less likely to be information free riders; they are more inclined than buyers of search goods to buy from the Web site from which they obtain the most product information. This finding echoes arguments presented by others (Alba et al. 1997; Lynch and Ariely 2000) that reducing the cost of searching for quality information lowers price sensitivity and provides an incentive for vendors of experience goods to provide this information.

Finally, we find evidence that consumer information search on the Internet is much more extensive than previously reported. Although prior research has suggested that online search is extremely limited (Brynjolfsson and Smith 2000; Johnson et al. 2004; Steckel et al. 2005), we find (even after discarding sessions with average page times in excess of 5 minutes) that though consumers only visit 3.4 domains, they spend an average of 78 minutes on product search and view an average of 124 Web pages for each transaction. Thus, although consumers do not engage in extensive comparison shopping across retailers, it seems evident that they engage in extensive online search. Further research could examine the different components of this search, including time spent gathering general information about the product category, time spent gathering specific information about products, and time spent completing transactions after product choice has been made. Such an analysis would require more detailed, page-level data.

From a theoretical standpoint, this article points to the continued relevance of the search/experience paradigm for consumer behavior. Importantly, it is no longer the amount of search or the perceived ability to assess product quality before purchase that distinguishes search from experience goods; rather, it is the type of information sought and the way this information is accessed and processed by the consumer. More generally, these results suggest a richer conceptualization of information search than that offered by traditional economic models (e.g., Stigler 1961), in which search is defined as the number of retailers from which price information is gathered and the costs of processing different types of information are assumed to be identical. By incorporating behavioral approaches, in which different types of information are associated with different decision processes and outcomes (Bettman et al. 1993; Häubl and Trifts 2000; Lurie 2004), this article offers insights not captured by traditional models of search.

Limitations

Although the preliminary experiment complements the browsing data by demonstrating differences between offline and online settings, college students are unlikely to have substantial experience with some of these products, which limits the ability to generalize the experimental results. In addition, although empirical data on the browsing behavior of a representative sample of U.S. consumers increase external validity, there are several limitations. In particular, we are unable to tell whether the differences we observe in search behavior for search and experience goods are due to differences in the type of information accessed, the way this information is presented by the seller, or the way this information is processed by the consumer. In particular, differences in the presentation of search and experience attributes on Web sites may drive the differences in search behavior that we observe. In addition, we are unable to separate experiential, nondirected behavior from goal-directed search (Hoffman and Novak 1996). Another limitation stems from the unavailability of URL information in our data set; instead, we are limited to domain-level information. The availability of URL information would permit a more detailed assessment of the underlying data viewed by the consumer (Montgomery et al. 2004). Perhaps further research could examine these issues experimentally, because increased privacy concerns make access to URL information unlikely.

Managerial Implications

We envision three broad implications of our empirical findings for marketing managers and Web site designers. First, differences in search and purchase characteristics between search and experience goods emphasize the need for differences in Web site design for the two product categories. For experience goods, consumers are likely to benefit from more complex and informative Web sites that incorporate multimedia presentations and consumer feedback to illustrate product features. For these goods, the Internet provides a convenient channel to disseminate quality information and "experience" the product before purchase. Second, because free riding is more acute for search than for experience goods, investments in superior and feature-rich Web sites are more valuable for vendors of experience goods. For search goods, investments in consumer feedback mechanisms may not be as important; vendors of search goods may benefit from strategies that enable them to sell at lower cost. For these goods, benefits accrue primarily to the consumer, perhaps necessitating an independent third party that provides such information for multiple vendors. In addition, retailers with sophisticated information technology infrastructures that incorporate consumer feedback, third-party recommendations, and multimedia presentations at the Web site will benefit more by focusing on experience than on search goods. Third, the availability of recommendations from other consumers has a greater impact on time spent at the Web site and purchase likelihood than third-party recommendations or multimedia content. This seems to be well understood by online vendors: Among the 667 vendors in our data set, approximately 36% implement consumer feedback systems, more than 10% present multimedia content, but less than 6% publish third-party recommendations.

Further Research

Further research could extend these results to other products and services. This might involve an examination of the theoretical antecedents, as in the experiment, or the behavioral consequences, as in the browsing, free-riding, and purchase behavior analyzed here. More generally, such an analysis would provide an important link among research on product characteristics, consumer perceptions, consumer behavior, and industry practices—variables that have typically been analyzed in separate research streams. Other research could examine the reasons consumers believe that they can or cannot evaluate product quality before purchase for different types of goods. Further research could also assess the extent to which differences in perception and behavior vary across consumers and are moderated by individual differences, such as involvement and risk aversion.

We draw on Nelson's (1970, 1974) original classification because of its extensive history in the marketing literature and to examine whether it provides insights into online consumer behavior. Our results show that Nelson's classification is still relevant in the online context. Despite its support in the prior literature and in the offline version of our preliminary experiment, the particulars of Nelson's classification of the six products in our study might be contested in two specific ways. First, it might be argued that cameras are search goods, because of attribute-driven benefits, and that garden and patio products are experience goods, because of their tactile nature. Using this alternative classification, we find stronger results in terms of number of pages searched and time per page. Second, it might be argued that other approaches to product classification—such as Peterson, Balasubramanian, and Bronnenberg's (1997) classification based on purchase frequency, tangibility, and differentiation or Weathers, Sharma, and Wood's (2007) classification based on the perceived need to see, touch, or hear a product versus read manufacturer-provided information about product attributes—are more relevant in the online context. As our preliminary experiment shows, using consumers' perceived ability to assess product quality as a mechanism for classifying search versus experience goods is indeed problematic because the results are contingent on the channel context and may be nondiagnostic in online settings (Weathers and Makienko 2006; Weathers, Sharma, and Wood 2007). Thus, further research could examine how alternative product classifications provide additional insights into online consumer behavior.

Other research could provide a more detailed assessment of the ways information is processed for experience versus search goods. For example, purchasers of experience goods may engage in more compensatory processing than purchasers of search goods. Process-tracing studies might be used to examine this issue. Furthermore, patterns of information search for experience and search goods may evolve differently over time as consumers become more conversant with online shopping and gain more product experience. In addition, online consumers' willingness to share their experiences suggests an opportunity to study postpurchase differences between search and experience goods. It is also important to assess whether our results are applicable to traditional retail environments, which often allow consumers to try out and experience products, and to examine in more detail the interplay between patterns of information search and purchase behavior across traditional and online channels. Finally, because our study reveals important differences in the mechanics of search between different products, further research could develop new product classifications based on how consumers search for and purchase products online.

REFERENCES

Alba, Joseph, John Lynch, Barton Weitz, Chris Janiszewski, Richard Lutz, Alan Sawyer, and Stacy Wood (1997), "Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces," *Journal of Marketing*, 61 (July), 38–53.

Bettman, James R., Eric J. Johnson, Mary Frances Luce, and John W. Payne (1993), "Correlation, Conflict and Choice," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 19 (July), 931–51.

———, ———, and John W. Payne (1990), "A Componential Analysis of Cognitive Effort in Choice," *Organizational Behavior and Human Decision Processes*, 45 (February), 111–39.

Bloom, Paul N. and James E. Pailin Jr. (1995), "Using Information Situations to Guide Marketing Strategy," *Journal of Consumer Marketing*, 12 (2), 19–27.

Brynjolfsson, Erik and Michael D. Smith (2000), "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science*, 46 (April), 563–85.

Bucklin, Randolph E. and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40 (August), 249–67.

Cameron, A. Colin and Pravin K. Trivedi (2005), *Microeconometrics: Methods and Applications*. New York: Cambridge.

Carlton, Dennis W. and Judith A. Chevalier (2001), "Free-Riding and Sales Strategies for the Internet," *Journal of Industrial Economics*, 49 (December), 441–61.

Chevalier, Judith A. and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345–54.

Coupey, Eloise (1994), "Restructuring: Constructive Processing of Information Displays in Consumer Choice," *Journal of Consumer Research*, 21 (June), 83–99.

Daft, Richard L. and Robert H. Lengel (1984), "Information Richness: A New Approach to Manager Information Processing and Organization Design," in *Research in Organization Behavior*, Vol. 6, Barry Staw and L.L. Cummings, eds. Greenwich, CT: JAI Press, 191–233.

Darby, Michael R. and Edi Karni (1973), "Free Competition and the Optimal Amount of Fraud," *Journal of Law and Economics*, 16 (April), 67–88.

Diehl, Kristin (2005), "When Two Rights Make a Wrong: Searching Too Much in Ordered Environments," *Journal of Marketing Research*, 42 (August), 313–22.

Ford, Gary T., Darlene B. Smith, and John L. Swasy (1988), "An Empirical Test of the Search, Experience and Credence Attributes Framework," in *Advances in Consumer Research*, Vol. 15, Michael J. Houston, ed. Provo, UT: Association for Consumer Research, 239–44.

———, ———, and ——— (1990), "Consumer Skepticism of Advertising Claims: Testing Hypotheses from Economics of Information," *Journal of Consumer Research*, 16 (March), 433–41.

Franke, George R., Bruce A. Huhmann, and David L. Mothersbaugh (2004), "Information Content and Consumer Readership of Print Ads: A Comparison of Search and Experience Products," *Journal of the Academy of Marketing Science*, 32 (Winter), 20–31.

Friestad, Marian and Peter Wright (1994), "The Persuasion Knowledge Model: How People Cope with Persuasion Attempts," *Journal of Consumer Research*, 21 (June), 1–31.

Garner, Wendell R. (1962), *Uncertainty and Structure as Psychological Concepts*. New York: John Wiley & Sons.

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545–60.

Greene, William H. (2003), *Econometric Analysis*, 5th ed. New York: McMillian.

Ha, Hong-Youl (2002), "The Effects of Consumer Risk Perception on Pre-Purchase Information in Online Auctions: Brand, Word-of-Mouth, and Customized Information," *Journal of Computer-Mediated Communication*, 8 (October), (accessed February 15, 2007), [available at http://jcmc.indiana.edu/vol8/issue1/ha.html].

Ha, Young-Won and Stephen J. Hoch (1989), "Ambiguity, Processing Strategy, and Advertising-Evidence Interactions," *Journal of Consumer Research*, 16 (December), 354–60.

Häubl, Gerald and Valerie Trifts (2000), "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science*, 19 (Winter), 4–21.

Hoch, Stephen J. and John Deighton (1989), "Managing What Consumers Learn from Experience," *Journal of Marketing*, 53 (April), 1–20.

——— and Young-Won Ha (1986), "Consumer Learning: Advertising and the Ambiguity of Product Experience," *Journal of Consumer Research*, 13 (September), 221–33.

Hoffman, Donna L. and Thomas P. Novak (1996), "Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations," *Journal of Marketing*, 60 (July), 50–68.

Hsieh, Yi-Ching, Hung-Chang Chiu, and Mei-Yi Chiang (2005), "Maintaining a Committed Online Customer: A Study Across Search-Experience-Credence Products," *Journal of Retailing*, 81 (1), 75–82.

Jacoby, Jacob, James J. Jaccard, Imran Currim, Alfred Kuss, Asim Ansari, and Tracy Troutman (1994), "Tracing the Impact of Item-by-Item Information Accessing on Uncertainty Reduction," *Journal of Consumer Research*, 21 (September), 291–303.

Johnson, Eric J., Steven Bellman, and Gerald L. Lohse (2003), "Cognitive Lock-In and the Power Law of Practice," *Journal of Marketing*, 67 (April), 62–75.

———, Wendy W. Moe, Peter S. Fader, Steven Bellman, and Gerald L. Lohse (2004), "On the Depth and Dynamics of Online Search Behavior," *Management Science*, 50 (March), 299–308.

——— and John W. Payne (1985), "Effort and Accuracy in Choice," *Management Science*, 31 (April), 395–414.

——— and Edward J. Russo (1984), "Product Familiarity and Learning New Information," *Journal of Consumer Research*, 11 (June), 542–60.

Johnson, Michael D. (1984), "Consumer Choice Strategies for Comparing Noncomparable Alternatives," *Journal of Consumer Research*, 11 (December), 741–53.

——— (1988), "Comparability and Hierarchical Processing in Multialternative Choice," *Journal of Consumer Research*, 15 (December), 303–314.

Klein, Lisa R. (1998), "Evaluating the Potential of Interactive Media Through a New Lens: Search Versus Experience Goods," *Journal of Business Research*, 41 (March), 195–203.

——— and Gary T. Ford (2003), "Consumer Search for Information in the Digital Age: An Empirical Study of Prepurchase Search for Automobiles," *Journal of Interactive Marketing*, 17 (Summer), 29–49.

Koch, James V. and Richard J. Cebula (2002), "Price, Quality, and Service on the Internet: Sense and Nonsense," *Contemporary Economic Policy*, 20 (January), 25–37.

Krishnan, Balaji C. and Michael D. Hartline (2001), "Brand Equity: Is It More Important in Services?" *Journal of Services Marketing*, 15 (5), 328–42.

Lurie, Nicholas H. (2004), "Decision Making in Information-Rich Environments: The Role of Information Structure," *Journal of Consumer Research*, 30 (March), 473–86.

——— and Charlotte H. Mason (2007), “Visual Representation: Implications for Decision Making,” *Journal of Marketing*, 71 (January), 160–77.
Lynch, John G. and Dan Ariely (2000), “Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution,” *Marketing Science*, 19 (Winter), 83–103.
Malhotra, Naresh K. (1982), “Information Load and Consumer Decision Making,” *Journal of Consumer Research*, 8 (March), 419–30.
Mayzlin, Dina (2006), “Promotional Chat on the Internet,” *Marketing Science*, 25 (March), 155–63.
Moe, Wendy W. (2003), “Buying, Searching, or Browsing: Differentiating Between Online Shoppers Using In-Store Navigational Clickstream,” *Journal of Consumer Psychology*, 13 (1–2), 29–39.
——— and Peter S. Fader (2004), “Dynamic Conversion Behavior at E-Commerce Sites,” *Management Science*, 50 (March), 326–35.
Montgomery, Alan L., Shibo Li, Kannan Srinivasan, and John C. Liechty (2004), “Modeling Online Browsing and Path Analysis Using Clickstream Data,” *Marketing Science*, 23 (Fall), 579–95.
Moore, William L. and Donald R. Lehmann (1980), “Individual Differences in Search Behavior for a Nondurable,” *Journal of Consumer Research*, 7 (December), 296–307.
Moorthy, Sridhar, Brian T. Ratchford, and Debabrata Talukdar (1997), “Consumer Information Search Revisited: Theory and Empirical Analysis,” *Journal of Consumer Research*, 23 (March), 263–77.
Morton, Fiona Scott, Florian Zettelmeyer, and Jorge Silva-Risso (2001), “Internet Car Retailing,” *Journal of Industrial Economics*, 49 (December), 501–519.
Nelson, Phillip (1970), “Information and Consumer Behavior,” *Journal of Political Economy*, 78 (March–April), 311–29.
——— (1974), “Advertising as Information,” *Journal of Political Economy*, 82 (July–August), 729–54.
Payne, John W., James R. Bettman, and Eric J. Johnson (1988), “Adaptive Strategy Selection in Decision Making,” *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14 (July), 534–52.
Peterson, Robert A., Sridhar Balasubramanian, and Bart J. Bronnenberg (1997), “Exploring the Implications of the Internet for Consumer Marketing,” *Journal of the Academy of Marketing Science*, 25 (Fall), 329–46.
Ratchford, Brian T., Myung-Soo Lee, and Debabrata Talukdar (2003), “The Impact of the Internet on Information Search for Automobiles,” *Journal of Marketing Research*, 40 (May), 193–209.
Schlosser, Ann E. (2003), “Experiencing Products in the Virtual World: The Role of Goal and Imagery in Influencing Attitudes Versus Purchase Intentions,” *Journal of Consumer Research*, 30 (September), 184–98.
———, Tiffany Barnett White, and Susan M. Lloyd (2006), “Converting Web Site Visitors into Buyers: How Web Site Investment Increases Consumer Trusting Beliefs and Online Purchase Intentions,” *Journal of Marketing*, 70 (April), 133–48.
Shannon, Claude Elwood and Warren Weaver (1949), *The Mathematical Theory of Communication*. Urbana: University of Illinois Press.
Shugan, Steven M. (1980), “The Cost of Thinking,” *Journal of Consumer Research*, 7 (September), 99–111.
Steckel, Joel H., Russell S. Winer, Randolph E. Bucklin, Benedict G.C. Dellaert, Xavier Drèze, Gerald Häubl, et al. (2005), “Choice in Interactive Environments,” *Marketing Letters*, 16 (3), 309–320.
Stigler, George J. (1961), “The Economics of Information,” *Journal of Political Economy*, 69 (June), 213–25.
Van Baal, Sebastian and Christian Dach (2005), “Free-Riding and Customer Retention Across Retailers’ Channels,” *Journal of Interactive Marketing*, 19 (Spring), 75–85.
Weathers, Danny and Igor Makienko (2006), “Assessing the Relationships Between E-Tail Success and Product and Web Site Factors,” *Journal of Interactive Marketing*, 20 (Spring), 41–54.
———, Subhash Sharma, and Stacy L. Wood (2007), “Effects of Online Communication Practices on Consumer Perceptions of Performance Uncertainty for Search and Experience Goods,” *Journal of Retailing*, 83 (4), 393–401.
West, Patricia M. and Susan M. Broniarczyk (1998), “Integrating Multiple Opinions: The Role of Aspiration Level on Consumer Response to Critic Consensus,” *Journal of Consumer Research*, 25 (June), 38–51.
Winer, Russell S. (1999), “Experimentation in the 21st Century: The Importance of External Validity,” *Journal of the Academy of Marketing Science*, 27 (Summer), 349–58.
Wood, Stacey L. and John G. Lynch Jr. (2002), “Prior Knowledge and Complacency in New Product Learning,” *Journal of Consumer Research*, 29 (3), 416–26.
Wooldridge, Jeffrey M. (2001), *Econometric Analysis of Cross Section and Panel Data*, 1st ed. Cambridge, MA: MIT Press.
Wright, Alice A. and John G. Lynch Jr. (1995), “Communication Effects of Advertising Versus Direct Experience,” *Journal of Consumer Research*, 21 (March), 708–718.
Zauberman, Gal (2003), “The Intertemporal Dynamics of Consumer Lock-In,” *Journal of Consumer Research*, 30 (December), 405–419.
Zettelmeyer, Florian, Fiona Scott Morton, and Jorge Silva-Risso (2006), “How the Internet Lowers Prices: Evidence from Matched Survey and Automobile Transaction Data,” *Journal of Marketing Research*, 43 (May), 168–81.