

Effect of Consumer Beliefs on Online Purchase Behavior: The Influence of Demographic Characteristics and Consumption Values[☆]

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Abstract

The three most common beliefs that consumers have about shopping online are that it saves time, saves money and helps find products that best match needs. But how do these beliefs, either individually or in combination, influence online purchase behavior? The premise of the article is that the effect of beliefs on online purchase behavior is moderated by demographic characteristics such as income, education, and generational age, and by consumption values such as the inclination to consider many alternatives before making a choice, the enjoyment of shopping, and the tendency to research products prior to making a purchase. The findings on how beliefs and consumption values influence purchase behavior can assist online retailers formulate product positioning strategies that create more value for consumer segments through better customization, thereby enhancing retailer profits. The findings can also help public policy makers design communication strategies to help lower-income consumers realize the same benefits of e-commerce as their higher-income counterparts.

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Due to the rapid growth of e-commerce, consumer purchase decisions are increasingly being made in online stores. In the 12 years that the U.S. Census Bureau has kept track, e-commerce sales have grown at a double-digit rate from \$5 billion in 1998 to an estimated \$160 billion in 2010 (http://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf). Based on the latest statistics, e-commerce sales registered a 14% increase in 3Q 2010 in comparison to a 4.0% increase in overall retail sales for the same period. Web-based stores offer immense choice and provide a “virtual” shopping experience that is more real-world than ever before, through the use interactive video, animation, flash, zoom, 3-D rotating images, and “live” online assistance.

Shopping on the Internet is commonplace. For example, in 2007, nearly 60% of American consumers used the Internet to

research products, while 50% made an online purchase. The Internet has made it easier for consumers to search for the best price when that is most important due to the profusion of merchants on the Web (Brynjolfsson and Smith 2000). The large selections offered by these merchants coupled with the ability of consumers to navigate through these product assortments have also made it easier to search for the best product fit (i.e., the match between product attributes and consumer needs) when that is most important. A study of new car buyers showed that consumers who shopped online paid \$450 less (on average) for their purchases (Scott Morton, Zettelmeyer, and Silva-Risso 2001). The increased variety provided by online merchants has given rise to the long-tail phenomenon (Brynjolfsson, Hu, and Smith 2006), where even the most demanding consumers can find products that closely match their needs. But the extent to which consumers realize these benefits depends on the beliefs they have about e-shopping, their demographic characteristics and their consumption values.

According to a 2008 report on “Online Shopping” from Pew Internet & American Life Project, the top three beliefs that consumers have about online shopping relate to saving time,

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finding a low price, and obtaining the best product fit, i.e., the match between product attributes and consumer needs (Horrigan 2008). Consumer beliefs can relate to either the benefits of online search or the costs of online search or both. Who are the consumers whose beliefs relate more to the cost of search (e.g., saving time) compared to those whose beliefs relate more to the benefit of search (e.g., finding a low price or obtaining the best product fit)? For example, do consumers with more income believe that online shopping saves times to a greater extent than their lower-income counterparts? And to what extent do these beliefs and related consumption values such as shopping enjoyment and the inclination to consider many alternatives before making a choice influence online purchase behavior?

An understanding of how beliefs and consumption values influence purchase behavior can assist online retailers to create more value for consumers thereby reducing their price sensitivity and enhancing retailer margins. Web customization strategies that are consistent with existing belief structures are also likely to enhance customer satisfaction, increase loyalty, and potentially lead to cognitive lock-in (Johnson, Bellman, and Lohse 2003). For example, consumers whose belief structures focus more on saving time could be presented with a customized product assortment generated by an adaptive Web design (Baraglia and Silvestri 2007; Goy, Ardissono, and Petrone 2007) that emphasizes time, convenience and ease of navigation, and de-emphasizes price. On the other hand, the same adaptive Web design could highlight low-priced products for consumers whose belief structures value saving money. Likewise, for consumers whose belief structures relate more to finding the best product fit, an adaptive Web design could be used to highlight the breadth, depth and the variety of the product assortment offered by the online merchant.

On the public policy front, past research indicates that certain segments of consumers may have benefited disproportionately more from the Internet than other groups (Zettelmeyer, Scott Morton, and Silva-Risso 2005; Pauly, Herring, and Song 2002). An understanding of how beliefs and consumption values influence purchase behavior could also be used by public policy makers to formulate communication strategies to help lower-income consumers realize the same benefits of e-commerce as their higher-income counterparts (Baye, Morgan, and Scholten 2003).

Relevant Literature

An important theme in research on online shopping has focused on belief–attitude–intention theories, such as the theory of reasoned action (Ajzen and Fishbein 1980), theory of planned behavior (Ajzen 1991), and the technology acceptance model (Davis 1993). The typical findings from these studies are that consumers beliefs relating to the perceived risk of e-shopping, the perceived usefulness, ease of use, and trust in the related Web technology influence online purchase intentions (Hansen, Jensen, and Solgaard 2004; Koufaris 2002; Van der Heijden, Verhagen, and Creemers 2003; Verhoef and Langerak 2001). The focus of the above studies has been on the

factors that influence the consumer decision to adopt online shopping either in conjunction with or as an alternative to traditional retail shopping. What is missing from this stream of research is how the content of beliefs relating to the phenomenon of interest (i.e., online shopping), rather than beliefs about the technology itself (i.e., perceived usefulness, ease of use) influences intentions and behavior.

The theory of consumption values (Sheth, Newman, and Gross 1991) provides an appropriate conceptual framework for filling this knowledge gap because it examines how consumption values and beliefs influence consumer decisions. For instance, how consumers allocate time, money and effort while shopping is a key tenet of the theory and has been mentioned as being “central to an understanding of consumer decision making” (Sheth, Newman, and Gross 1991, p 8). The consumer beliefs examined in this research directly relate to the use of these scarce resources.

A related stream of research on shopping orientations has found that consumer predispositions toward online shopping influence online purchase (Childers et al. 2001; Li, Kuo, and Russell 1999). Based on a review of 65 empirical studies on online shopping, a distinction has been drawn between time-conscious and price-conscious shoppers (Cao and Mokhtarian 2005). To the above classification, we add product-fit conscious consumers as a third category because recent research has found that the adoption of long-tail strategies by online retailers (Brynjolfsson, Hu, and Smith 2006; Hofacker 2008) has made it possible for online shoppers to increasingly focus on finding products that best match needs (Atkinson et al. 2010). The consumer beliefs examined in this research are closely linked to the shopping orientations mentioned above.

Theoretical Approach and Hypotheses

The purpose of the research is to investigate how consumer beliefs about the potential benefits of online shopping (e.g., saving time, saving money, finding a product that matches needs) influence online purchase behavior, and how the relationship between consumer beliefs and online purchase behavior is moderated by consumer characteristics such as income, education, and generational age, and by consumption values such as the inclination to consider many alternatives before making a choice, the enjoyment of shopping, and the tendency to research products prior to making a purchase. As a baseline prediction we expect that all three beliefs examined in this research will be positively related to online purchase behavior. The more important question is how these primary effects are influenced by consumer characteristics and consumption values. A related question is whether consumers who believe that online shopping saves time also believe that it saves money and enables finding products that best match needs? Or is there an implicit trade-off built into consumer belief structures, so that consumers who think that online shopping saves time believe that it saves money to a lesser degree?

To consider both the primary and secondary effects in a comprehensive manner, a cross-disciplinary approach based on

concepts from economics, mental accounting, cognitive psychology, and the consumption values literature is used to formulate the hypotheses. By so doing, a more theory-driven understanding of how consumer characteristics and beliefs influence online purchase behavior can be obtained. There have only been a few attempts to examine online shopping from a perspective that cuts across traditional disciplinary boundaries.

Economic Perspective

The relationship between income and online shopping intentions has generally been found to be positive (Donthu and Garcia, 1999; Li, Kuo, and Russell 1999; Mathwick, Malhotra, and Rigdon 2001). But what has yet to be investigated is how beliefs relating to saving time and money potentially moderate this relationship. According to the economic perspective, higher-income consumers value their time more because of its opportunity cost (Goldman and Johansson 1978; Ratchford, Lee, and Talukdar 2003; Stigler 1961). Hence, they are more likely to have a “time conscious” shopping orientation and a stronger belief that online shopping saves time. On the other hand, lower-income consumers are more likely to have a “price conscious” shopping orientation and a stronger belief that online shopping saves money. But, higher-income consumers are also known to derive a greater benefit from online services (Lambrecht and Seim 2006). Hence, economic theory predicts that consumers will possess consumption values and beliefs that make an implicit trade-off between the benefits of search (e.g., money saved) and the costs of search (e.g., time spent) based on the economic value of their time, which in turn will be based (approximately) on their income. Consumers who are “income rich and time poor” may adopt a shopping orientation that relates to saving time, while those who are “time rich, but income poor” may adopt a shopping orientation that relates to saving money, leading to the following hypotheses:

H1. The positive relationship between the belief that online shopping saves time and purchase behavior will be stronger for higher-income consumers in comparison to lower-income consumers.

H2. The positive relationship between the belief that online shopping saves money and purchase behavior will be stronger for lower-income consumers in comparison to higher-income consumers.

Mental Accounting Perspective

The mental accounting model has been used to understand how consumers make trade-offs between scarce resources. It proposes that consumers create separate “mental accounts” for scarce resources such as time and money and then have difficulty moving these resources between accounts (LeClerc, Schmitt, and Dube 1995; Thaler 1999). In other words, consumers may have one mental account for “spending time” and a different one for “saving money.” Consumers may then

segregate (i.e., compartmentalize) beliefs relating to saving money and saving time in a similar manner and hence *not* use the economic value of time to make the implicit trade-off between the costs of search (e.g., time spent) and the benefits of search (e.g., money saved), as in the economic perspective (Okada and Hoch 2004). Rather, online purchase behavior may be based on the relative salience of the beliefs relating to saving time and saving money, independent of economic considerations. It is possible that some consumers may have several beliefs relating to “spending time” that enable them to distinguish between low-value and high-value online pursuits (Duxbury et al. 2005).

The mental accounts consumers have are likely to be influenced by the frequency and type of Internet usage. Lower-income consumers are less likely to use the Internet at work and also more likely to use it for recreation (Comor 2000; Goldfarb and Prince 2008) which makes it difficult for them to distinguish between low-value and high-value online pursuits. In other words, they are more likely to consolidate time spent on all online activities into a single mental account. Hence, they are less likely to have a “time is money” orientation. In contrast, higher-income consumers are more likely to have separate mental accounts for time spent on low-value versus high-value online activities because they are more likely to use the Internet at work (Goldfarb and Prince 2008) and also more likely to use it for consumption (Comor 2000). Consequently, they are more likely to have a “time is money” orientation while shopping online.

H3. The positive relationship between the belief that online shopping saves time and purchase behavior will be stronger for consumers who use the Internet more frequently in comparison to those who use the Internet less frequently.

There are also important generational differences in the use of the Internet (Mathwick, Malhotra, and Rigdon 2001). Thus, it is possible that generational age potentially influences the mental accounts of online shoppers. Younger consumers (e.g., Gen Y and Gen X) are almost always “connected” and lead wired lifestyles. Hence, they are more likely to believe that online shopping saves money because they are likely to be adept at using recommendation agents and Web 2.0 social media to find bargains. Older consumers (e.g., leading boomers and matures) are less likely to share the same belief due to slower adoption rates for new information and communication technologies (Gilly and Zeithaml 1985; Phillips and Sternthal, 1977).

H4. The positive relationship between the belief that online shopping saves money and purchase behavior will be stronger for younger consumers in comparison to older consumers.

Cognitive Psychology Perspective

The effort-accuracy framework has been used to understand how consumers balance effort reduction with accuracy improvement goals (Bellman et al. 2006; Payne, Bettman, and Johnson 1993). Time costs are generally lower, while cognitive

costs are potentially higher in online settings (Bellman et al. 2006). Thus, in the online shopping context, consumers may form beliefs that make an implicit trade-off between effort (e.g., time spent) against accuracy (e.g., product fit obtained) based on effort-accuracy considerations. The empirical research on the effort-accuracy framework suggests that the trade-off between accuracy improvement (e.g., product fit obtained) and effort reduction (e.g., time saved) is uneven. Consumers focus more on effort reduction rather than on accuracy improvement goals in offline settings due to cognitive limitations. In an online setting, electronic decision aids (i.e., recommendation agents, shopbots) augment the cognitive capabilities of consumers. Thus, consumers beliefs relating to the benefits of search (e.g., product fit obtained) may be more salient than beliefs relating to the costs of search (e.g., time spent). But, not all consumers may re-calibrate their belief structures in such a manner.

Previous research has found that consumers with more education engage in an extended search for information and make greater use of information (Beatty and Smith 1987; Mathwick, Malhotra, and Rigdon 2001). Hence, they are more likely to believe that online shopping makes it easier to locate hard-to-find products. Further, consumers with more education are more likely to have the cyber fluency or Web expertise (i.e., device knowledge) needed to become skillful at using electronic decision aids to find products that best match needs.

H5. The positive relationship between the belief that online shopping helps find the best product fit and purchase behavior will be stronger for consumers with more education in comparison to consumers with less education.

Consumption Values Perspective

According to the theory of consumption values (Sheth, Newman, and Gross 1991) consumers seek both functional and hedonic values while shopping. Consumers who focus more on the functional aspects of shopping are more likely to consider many product alternatives prior to making a choice. But, the desire to examine a broad selection of products has to be balanced with the time needed to do so. The paradox has been labeled the “tyranny of choice” (Schwartz 2004) because choosing an option forecloses the selection of other options that may be nearly as attractive. Hence, the positive relationship between the belief that online shopping saves time and online purchase behavior is likely to be weaker for consumers who like many choices because these consumers are more likely to encounter the “tyranny of choice” phenomenon.

H6. The positive relationship between the belief that online shopping saves time and online purchase behavior will be weaker for shoppers who like many choices.

Consumers who focus more on the hedonic value of shopping are more likely to enjoy shopping (Hoffman and Novak 1996). The belief that online shopping helps find products that best match needs is likely to be more salient for these consumers. Since they also obtain hedonic value while

looking for a good product fit, the positive relationship between the belief that online shopping helps find the best product fit and online purchase behavior is likely to be stronger for these consumers (Childers et al. 2001; Mathwick, Malhotra, and Rigdon 2001).

H7. The positive relationship between the belief that online shopping helps find the best product fit and online purchase behavior will be stronger for shoppers who enjoy shopping.

Consumers who focus more on the functional aspects of shopping are more likely to research products prior to making a purchase. The belief that online shopping helps saves time is likely to be less salient for these consumers. They are more likely to focus on the benefits of search (i.e., product fit obtained) rather than on the costs of search (i.e., time spent). Hence, the relationship between the belief that online shopping saves time and online purchase behavior is likely to be weaker for them.

H8. The positive relationship between the belief that online shopping saves time and online purchase behavior will be weaker for shoppers who like to research products.

Data

The data used to test the hypotheses are based on telephone interviews of a national sample of 1684 Internet users, 18 years and older, in the continental United States, conducted by a leading American survey research organization in 2007, on behalf of Pew Internet & American Life Project (www.pewinternet.org). Data provided by the Pew Internet organization are used by researchers in academia, industry and by government policy makers. They are widely regarded as an authoritative source of information on how Americans use the Internet. For example, a recent US government policy report issued by the Federal Communications Commission (FCC) titled “Connecting America” is based on data provided by the Pew Internet organization.

The sample of 1684 Internet users was a sub-set of a larger sample of 2400 respondents that corresponded to the general population. A screening question (Do you use the Internet at least occasionally?) was used as the basis for selecting the study sample. Interviews with the 716 respondents who were not Internet users were terminated at the end of the screening question. Hence the study population may be defined as Internet users, 18 years and older in the continental United States in 2007. The telephone interviews were conducted using a dual-frame sample design. Both landline and cellular random-digit dial (RDD) samples were used. The landline sample was a list-assisted random digit sample of telephone numbers selected from landline telephone exchanges in the continental United States. The cell phone sample was drawn from dedicated cellular exchanges based on the most recently available TPM (Terminating Point Master) data file.

For the landline sample, interviewers asked to speak with the youngest male currently at home. If no male was available,

interviewers asked to speak with the youngest female at home. This systematic respondent selection technique has been shown to produce samples that closely mirror the population in terms of age and gender. For the cell phone sample, interviews were conducted with whoever answered the cell phone as long as they were an adult. At least 10 attempts were made to complete an interview for each sampled phone number. Calls were staggered over times of day and days of the week to maximize the chance of making contact with potential respondents. Each sampled phone number received at least one daytime call in an attempt to make contact with a respondent.

Of the working phone numbers in the combined sample (landline plus cell phone), 78% were contacted by an interviewer and 28% agreed to participate in the survey. Eighty-two percent were found eligible for the interview. Furthermore, 90% of eligible respondents completed the interview. Therefore, the final response rate calculated as the product of the contact rate, cooperation rate and completion rates was 20%. The margin of sampling error is ± 2.7 percentage points for the sample of 1684 Internet users used to test the hypotheses.

The data were weighted to help correct for potential bias that might be introduced due to non-response and to account for the dual-frame sample design. The demographic weighting parameters were derived by using the Census Bureau's March 2006 Annual Social and Economic Supplement Survey to produce population parameters for the demographic characteristics of adults 18 or older living in the continental United States. First, the population parameters were compared with the sample characteristics to construct sample weights. Then, the data were weighted to bring the demographic characteristics of the sample into alignment with the population parameters using an iterative technique that simultaneously adjusts the distribution of all demographic weighting parameters.

The questionnaire was administered using professionally trained and experienced personal interviewers from a leading survey organization. Information on the constructs in the study was gathered through both pre-coded and open-ended responses. The likelihood that respondents made recall errors was minimized by asking respondents to report online behavior and activities in which they had recently engaged. Further, based on key comparisons on online usage and experiences between the sample and similar data from other surveys conducted by Pew Internet, no evidence of any systematic error in the data was found. Because of these validity checks and the use of professional interviewers trained to probe and record respondent behavior, it was felt that the data were of sufficiently high quality to merit their use in testing the hypotheses.

Measures

The primary dependent variable *Online Shopper* was operationalized using answers to two dichotomous scales (1 = yes; 0 = no) that asked whether respondents had "looked for information online about a product or service" and "bought a product online." Respondents who provided affirmative (i.e., yes) answers to both questions were regarded as being an online

shopper. The three main consumer beliefs regarding online shopping, *Saves Time*, *Saves Money*, and *Helps Find Best Product Fit* were measured by asking respondents to express agreement with the statements "shopping online saves me time," "the Internet is the best place to find bargains," and "the Internet is the best place to buy items that are hard to find," respectively, using four-point Likert type scales (1 = strongly disagree; 2 = disagree; 3 = agree; 4 = strongly agree). The consumer belief statements were embedded in a larger set of statements that corresponded to other online shopping beliefs, such as the need for seeing and touching products prior to purchase and the willingness to provide credit card or personal information online.

The primary independent variable of interest was *Income*. It was measured as the total household income from all sources before taxes in 2006. To reduce potential over-reporting bias, respondents were first asked to indicate whether their income level was above or below \$40,000. Depending on their response, they were then presented income categories that were appropriate for the income level indicated. A seven-point ordinal scale (1 = less than \$10,000; 2 = \$10,000 to \$20,000; 3 = \$20,000 to \$30,000; 4 = \$30,000 to \$40,000; 5 = \$40,000 to \$60,000; 6 = \$60,000 to \$100,000; 7 = more than \$100,000) was constructed by concatenating the categories presented to the below \$40,000 and above \$40,000 income groups. *Generational Age* was measured using a six point ordinal scale that used break-points in chronological age that are normally used by demographers to distinguish between generations {1 = gen Y (18–30 years); 2 = gen X (31–42 years); 3 = trailing boomers (43–52 years); 4 = leading boomers (53–61 years); 5 = matures (62–71 years); 6 = after work (72+ years)}. *Education* was measured using a five-point ordinal scale (1 = less than high school; 2 = high school graduate; 3 = some college or vocational school graduate; 4 = college graduate; 5 = graduate school or advanced degree). *Internet Usage* which represented the frequency with which the respondent used the Internet at work or at home was measured using a five-point ordinal scale (1 = once every few weeks; 2 = 1–2 times a week; 3 = 3–5 times a week; 4 = about once a day; 5 = many times a day). Finally, respondent views regarding whether they enjoyed shopping, liked having many choices while shopping, and liked to research products prior to purchase were measured using three dichotomous variables (1 = yes; 0 = no) and labeled *Enjoy Shopping*, *Like Many Choices* and *Like to Research*.

Results

The sample distribution for the dependent variable, *Online Shopper*, showed 61% of the respondents had looked for information and bought a product online. For the consumer beliefs regarding online shopping, *Saves Time*, *Saves Money*, and *Helps Find Best Product Fit*, 73%, 52%, and 81% of the respondents, respectively, expressed agreement with them. The modal *Income* and *Education* categories were \$60,000 to \$100,000 of annual household income, and some college or vocational school, respectively. The modal category for

Generational Age was Trailing Boomers (43–52 years). Moderately high levels of *Internet Usage* were reported by the sample, with 52% of the respondents reporting Internet use many times a day. For *Enjoy Shopping*, *Like Many Choices* and *Like to Research*, 46, 80, and 79 of the respondents indicated that they enjoyed shopping, liked having many choices, and liked to research products, respectively. The incidence of missing values due to non-response for the study variables (expressed as percentages) was as follows: *Online Shopper* (0.5), *Saves Time* (8.3), *Saves Money* (11.9), and *Helps Find Best Product Fit* (7.4), *Income* (20.8), *Education* (0.8), *Generational Age* (3.1), *Internet Usage* (1.0), *Enjoy Shopping* (9.7), *Like Many Choices* (8.0), and *Like to Research* (4.2).

Overall, the sample distributions on the study variables closely matched the demographic profile of the American population with an Internet connection, as expected, due to the use of a national sample frame and probability sampling. Descriptive statistics on all study variables are reported in Table 1.

Table 1
Descriptive sample information.

	Frequency	(Valid Percent)
Online shopper:		
No	655	(39.1)
Yes	1021	(60.9)
Consumer beliefs *		
Saves time	1129	(73.1)
Saves money	766	(51.6)
Helps find best product fit	1263	(81.0)
Consumption values *		
Enjoy shopping	704	(46.3)
Like many choices	1243	(80.2)
Like to research	1270	(78.7)
Income:		
Less than \$10,000	56	(4.2)
\$10,000 to \$20,000	79	(5.9)
\$20,000 to \$30,000	156	(11.7)
\$30,000 to \$40,000	120	(9.0)
\$40,000 to \$60,000	290	(21.7)
\$60,000 to \$100,000	352	(26.4)
More than \$100,000	281	(21.1)
Generational age:		
Generation Y (18–30)	332	(20.4)
Generation X (31–42)	327	(20.0)
Trailing boomers (43–52)	365	(22.4)
Leading boomers (53–61)	291	(17.8)
Matures (62–71)	208	(12.8)
After work (72+)	108	(6.6)
Education:		
Less than High School	66	(3.9)
High School graduate	434	(26.0)
Some college or Vocational school	501	(30.0)
College graduate	380	(22.7)
Graduate school or Advanced degree	290	(17.4)
Internet Usage:		
Once every few weeks	158	(9.5)
1–2 times a week	146	(8.8)
3–5 times a week	212	(12.7)
About once a day	289	(17.3)
Many times a day	863	(51.7)

* Entries for Consumer Beliefs and Consumption Values are percentage affirmative (yes) responses.

Hypotheses tests

Logistic regression analysis was used to test the hypothesized relationships by adopting procedures for testing moderating effects that have been discussed in the literature (Aiken and West 1991; Cohen 1978; Finney et al. 1984; Hays 1988; Jaccard, Turrisi, and Wan 1990). First, *Online Shopper* was used as the dependent variable, while the three consumer beliefs about online shopping *Saves Time*, *Saves Money*, and *Helps Find Best Product Fit* were used as independent variables in a main effects only model. The demographic variables *Income*, *Education*, *Generational Age*, *Internet Usage* and consumption values *Like Many Choices*, *Enjoy Shopping*, *Like to Research* were entered as control variables into the logistic regression equation, so that the effects of the consumer beliefs of interest on *Online Shopper* could be interpreted as being in addition to the effect of demographic characteristics and consumption values that are related to e-shopping. Consistent with prior research and as expected, *Income* ($\beta = .15$; Wald's statistic = 8.98; $p < .01$), *Education* ($\beta = .20$; Wald's statistic = 5.86; $p < .05$) and *Internet Usage* ($\beta = .32$; Wald's statistic = 25.12; $p < .01$) were found to be positively related to *Online Shopper*, while a negative relationship was observed for *Generational Age* ($\beta = -.13$; Wald's statistic = 4.90; $p < .05$). Significant positive relationships with *Online Shopper* were also observed for the consumer beliefs *Saves Time* ($\beta = .97$; Wald's statistic = 26.96; $p < .01$) and *Helps Find Best Product Fit* ($\beta = .96$; Wald's statistic = 18.71; $p < .01$). The relationship between *Saves Money* and *Online Shopper* failed to achieve statistical significance ($\beta = .02$; Wald's statistic = 0.01; n.s.). The -2 log likelihood difference between a null (i.e., intercept only) and the main effects model indicated a significant fit ($\chi^2 = 906.44$; 13 df; $p < .01$) with a Cox and Snell $R^2 = .19$, as shown in Table 2. Further examination of the Odds Ratio coefficient for *Saves Time* showed that respondents who held this belief were

Table 2
Logistic regression model: main effects. Dependent variable: online shopper.

	β	Wald's Statistic	Significance	Exp (B)
Online shopping beliefs				
Saves time	0.97	26.96	$p < .01$	2.6
Saves money	0.02	0.01	n.s.	1.0
Helps find best product fit	0.96	18.71	$p < .01$	2.6
Demographics				
Income	0.15	8.98	$p < .01$	1.2
Education	0.20	5.86	$p < .05$	1.2
Generational age	-0.13	4.90	$p < .05$	0.9
Internet usage	0.32	25.12	$p < .01$	1.4
Consumption Values				
Like many choices	0.31	2.57	$p < .10$	1.4
Enjoy shopping	0.34	4.59	$p < .05$	1.4
Like to research	0.38	4.23	$p < .05$	1.5
Goodness-of-fit statistics				
-2 Log likelihood	906.44			
Model χ^2 (df = 10)	199.01			
Significance	$p < .01$			
Cox and Snell R^2	0.19			
McFadden R^2	0.17			

approximately two-and-a-half times more likely [(Exp (β)=2.6] to have positive *Online Shopper*. Similarly, an examination of the Odds Ratio coefficient for *Helps Find Best Product Fit* showed that these respondents were also roughly two-and-a-half times more likely [(Exp (β)=2.6] to have positive *Online Shopper*. Hence, it appears that the consumer beliefs about online shopping *Saves Time* and *Helps Find Best Product Fit* are the primary drivers of *Online Shopper*.

Next, the hypothesized interaction terms *Saves Time* \times *Income* (H1), *Saves Money* \times *Income* (H2), *Saves Time* \times *Internet Usage* (H3), *Saves Money* \times *Generational Age* (H4), *Helps Find Best Product Fit* \times *Education* (H5), *Saves Time* \times *Like Many Choices* (H6), *Helps Find Best Product Fit* \times *Enjoy Shopping* (H7), and *Saves Time* \times *Like to Research* (H8) were added to the main effects model to test for the hypothesized moderating influences of consumer beliefs and consumption values. No control variables were entered into the logistic regression equation this time, because as discussed Aiken and West (1991), some researchers have proposed this may be a better option for testing interaction effects, particularly when there is no theoretical prediction of main effects, non-experimental observational or survey data are being analyzed, and the theoretically predicted interaction effects are non-linear (Cohen 1978; Finney et al. 1984; Hays 1988). The logic for such an approach is that variance cannot be unambiguously partitioned between main and interaction effects in these situations.

A statistically significant interaction model would indicate the presence of hypothesized moderating effects. As before, significant positive relationships with *Online Shopper* were observed for *Saves Time* ($\beta = -1.13$; Wald's statistic=3.99; $p < .05$) and *Helps Find Best Product Fit* ($\beta = -0.80$; Wald's statistic=3.41; $p < .10$), but not *Saves Money* ($\beta = -0.24$; Wald's statistic=0.24; n.s.). The relationship between *Online Shopper* and the interaction term *Saves Time* \times *Income* (H1) and was significant ($\beta = .17$; Wald's statistic=4.49; $p < .05$) as were the relationships between *Online Shopper* and the interaction terms *Saves Time* \times *Internet Usage* (H3) ($\beta = .41$; Wald's statistic=25.93; $p < .01$) and *Helps Find Best Product Fit* \times *Education* (H5) ($\beta = .24$; Wald's statistic=7.52; $p < .01$). The relationship between the interaction terms *Saves Money* \times *Income* and *Saves Money* \times *Generational Age* and *Online Shopper* failed to achieve statistical significance. Nevertheless, the -2 log likelihood difference between a null (i.e., intercept only) and the hypothesized interactions model indicated a significant fit ($\chi^2 = 898.35$; 12 df; $p < .01$) with a Cox and Snell $R^2 = .20$, as shown in Table 3.

An examination of the logistic regression coefficients for the significant interactions showed that moderating effects of *Income*, *Education*, *Internet Usage*, *Generational Age*, *Enjoy Shopping* and *Like Many Choices* on *Saves Time*, *Saves Money*, and *Helps Find Best Product Fit* were in the predicted direction. For example, an examination of the Odds Ratio coefficient for the *Saves Time* \times *Income* interaction showed that higher-income respondents who held the belief that online shopping saves time were 1.2 times more likely [(Exp (β)=1.2] to have positive *Online Shopper* than lower-income respondents who held the same belief. Similarly, an examination of the Odds Ratio

Table 3

Logistic regression model: hypothesized interactions. Dependent variable: online shopper.

	β	Wald's	Significance	Exp (β)
Online shopping beliefs				
Saves time	-1.13	3.99	$p < .05$	0.3
Saves money	0.24	0.24	n.s.	1.3
Helps find best product fit	-0.80	3.41	$p < .10$	0.5
Beliefs \times demographics				
Saves time \times income (H1)	0.17	4.49	$p < .05$	1.2
Saves money \times income (H2)	-0.02	0.04	n.s.	1.0
Saves time \times internet usage (H3)	0.41	25.93	$p < .01$	1.5
Saves money \times generational age (H4)	-0.06	0.55	n.s.	0.9
Helps find best fit \times education (H5)	0.24	7.52	$p < .01$	1.3
Beliefs \times consumption values				
Saves time \times like many choices (H6)	0.44	3.31	$p < .10$	1.5
Helps find best fit \times enjoy shopping (H7)	0.54	8.70	$p < .01$	1.7
Saves time \times like to research (H8)	-0.71	3.61	$p < .05$	0.5
Goodness-of-fit statistics				
-2 Log Likelihood		898.35		
Model χ^2 (df=12)		207.10		
Significance		$p < .01$		
Cox and Snell R^2		0.20		
McFadden R^2		0.18		

coefficient for the *Saves Time* \times *Internet Usage* interaction showed that high Internet usage respondents who held the belief that online shopping saves time, were also one-and-a-half times more likely [(Exp (β)=1.5] to have positive *Online Shopper* than low Internet usage respondents who held the same belief.

The results of the logistic regression analyses seem to provide strong support for H1, H3, H5, H7, and H8, marginal support for H6, and no support for H2 and H4.

Discussion

The empirical findings show that the consumer beliefs about online shopping *Saves Time* and *Helps Find Best Product Fit* have a direct effect on *Online Shopper*, as well as an indirect effect when considered in combination with consumer characteristics and consumption values, while the consumer belief *Saves Money* only has a direct effect. At first thought, this result may appear to be somewhat troubling because of the widely held belief that prices in online stores are typically lower than in traditional retail stores. But, it is precisely that fact that causes the belief *Saves Money* not to vary across the consumer characteristics and consumption values examined in the hypotheses. Thus, on second thought, it is not surprising that the hypothesized interactions *Saves Money* \times *Income* (H2) and *Saves Money* \times *Generational Age* (H4) were not significant, as reported in Table 3.

Two observations can be made about the hypothesized interactions between consumer beliefs and consumption values that were found to be significant, namely, *Helps Find Best Product Fit* \times *Enjoy Shopping* (H7) and *Saves Time* \times *Like to Research* (H8). First, the belief that online shopping helps find products that best match needs seems to be more salient for consumers who enjoy shopping. Thus, consumers may be able to obtain both hedonic value (i.e., enjoyment of shopping) and

functional value (i.e., finding the best product fit) at the same time while shopping online. Second, the belief that online shopping saves time appears to be *less* salient for consumers who have tendency to research products (because of the negative logistic regression coefficient). In this instance, there appears to be a trade-off between a belief (i.e., saves time) and a functional value (i.e., tendency to research products).

Further analysis was conducted to investigate the hypothesized interactions relating to the two consumer beliefs about online shopping that were found to be significant, namely, *Saves Time* and *Helps Find the Best Product Fit*. Consumers who believe that online shopping *Saves Time* are different from those who believe that it *Helps Find Best Product Fit* because they are focusing on the cost of search (i.e., time spent) while the others are focusing on the benefit of search (i.e., product fit obtained). As previously noted, 73% of the respondents believe that online shopping *Saves Time*, while 81% believe that it *Helps Find Best Product Fit*. So, who are these consumers?

Profiling Online Shoppers

An analysis to profile consumers whose belief structures included the beliefs *Saves Time* and *Helps Find Best Product Fit* was conducted. Respondents were partitioned into three segments based on whether they believed that online shopping *Saves Time* and *Helps Find Best Product Fit*, or *Helps Find Best Product Fit*, or *Saves Time*. The results of the profile analysis are reported in Table 4. They show that consumers who believe that online shopping *Saves Time* tend to older (Kruskal–Wallis $\chi^2=30.7$; $p<.01$), with higher incomes (K–W $\chi^2=24.9$; $p<.01$), and more education (K–W $\chi^2=30.9$; $p<.01$), and use the Internet more frequently (Kruskal–Wallis $\chi^2=57.0$; $p<.01$), than those who believe that online shopping *Helps Find Best Product Fit*.

Thus, generational age, income, education, and extent of Internet usage influence whether consumers beliefs primarily relate to the costs (e.g., time spent) or the benefits (e.g., product fit obtained) of search. Further, the results show that consumers whose belief structures make an implicit trade-off between the

costs and benefits of search by believing that online shopping *Saves Time* and *Helps Find Best Product Fit* have a tendency to research products prior to making a purchase ($F=3.3$; $p<.05$) and like having many choices while shopping ($F=3.4$; $p<.05$) in comparison to those who belief structures relate to either the costs or the benefits of search, but not both, as shown in Table 4. Interestingly, these consumers are least likely to be affected by the “tyranny of choice” phenomenon (Schwartz 2004), because they are the most confident about their purchases ($F=51.6$; $p<.01$), and least overwhelmed by the amount of information available online ($F=2.9$; $p<.05$). These findings have important implications from a public policy perspective, because they suggest that consumers whose belief structures relate to *both* the costs and the benefits of search seem to be in the best position to make better quality decisions.

Limitations

The study was based on data that were collected by a survey rather than in a controlled laboratory setting. The “hit” rate for the hypothesized relationships being supported (6 out of 8) was lower than expected, possibly due to the cross-sectional nature of the data. Hence, due caution should be observed in drawing causal inferences. Despite this limitation, the results provide some novel insights into the belief structures of online shoppers and how they differentially influence online purchase behavior for various consumer segments. The study is very high in external validity because it is based on the real-world behavior of a nationally representative sample of American consumers with Internet access in 2007. To achieve the high degree of external validity some compromises had to be made during the data collection process. Some of the variables were measured using only two-point scales. While multiple indicators and scales would have been preferred, the extent to which repeated measurements of the same underlying behavior might cause respondent fatigue and lead respondents to prematurely terminate the phone interview is always an important consideration in survey research.

Table 4
Online shopping beliefs segment profiles.

	Segment focus on:			
	Helps find best fit and saves time	Helps find best fit	Saves time	
Demographic				
Income	\$60–100 K	\$40–60 K	More than 100 K	$\chi^2=24.9$ ($p<.01$)
Education	Some college	High school graduate	Some college	$\chi^2=30.9$ ($p<.01$)
Generational age	Trailing boomers	Gen Y	Trailing boomers	$\chi^2=30.7$ ($p<.01$)
Internet usage	Many times a day	About once a day	Many times a day	$\chi^2=57.0$ ($p<.01$)
Consumption values				
Like many choices	83%	79%	82%	$F=3.4$ ($p<.05$)
Enjoy shopping	49	51	47	$F=2.0$ ($p<.10$)
Like to research	81	73	79	$F=3.3$ ($p<.05$)
Subjective outcomes				
Overwhelmed with amount of information	28%	35%	37%	$F=2.9$ ($p<.01$)
Confident about purchase	90	71	81	$F=51.6$ ($p<.01$)

Note: entries are modal response categories for Demographic variables and percentage affirmative (yes) responses for Consumption values and Subjective outcomes.

Summary and Conclusions

The average American has less free time than in any period in modern history (Comor 2000). Shopping on the Internet normally takes less time than shopping in traditional retail outlets because of the time-consuming activities associated with the latter, e.g., driving to the store, waiting in line at the check-out, etc. (Bellman, Lohse, and Johnson 1999). An understanding of how consumer beliefs about the potential benefits of online shopping (e.g., saving time, saving money, finding a product that matches needs) influence the consumer decision to shop online for different consumer segments is therefore invaluable to online retailers as they seek to expand the pool of online shoppers (Montgomery and Smith 2009). An understanding of how the beliefs–behavior relationships for different demographic segments lead consumers to adopt a time-conscious, price conscious or product-fit conscious shopping orientation can help online retailers implement segmentation strategies that create more value for the three target segments, thereby enabling them to enhance margins by being able to price their product assortments to capture the added value created, or at least prevent the “commoditization” of their products. Online merchants can also select a product mix and delivery options that are in sync with the product fit, money saving, and time saving beliefs of consumers.

For online merchants, whose positioning strategies seem to focus on a particular segment (e.g. the online Walmart store and the price-conscious segment), information on how consumer beliefs relating to saving money vary across their customer base would be invaluable in making product assortment decisions, such as the depth of the assortment at key price-points. Recent developments in adaptive Web design (Baraglia and Silvestri 2007) and the use of RFID tagging has enabled retailers to significantly expand the personalization and customization strategies that can be deployed online. An awareness of the belief–intention relationships for different segments of shoppers can also help online retailers implement promotional and advertising strategies that are in tune with existing consumer belief structures, thereby cutting through online media “clutter” and enhancing message effectiveness.

The findings indicate that the belief structures of higher-income online shoppers relate to the time-savings features of Web-based shopping environment to a greater extent than lower-income consumers. Similarly, the belief structures of online shoppers with more education relate to the potential these environments offer in finding products that best match needs to a greater extent than shoppers with less education. Consumer characteristics such as generational age, degree of Internet usage, whether consumers like to have many choices, and whether they enjoy shopping moderate the relationships between consumer beliefs and online purchase behavior.

While higher-income consumers exhibit a strong tendency toward the belief that online shopping saves time, the relationship between income level and beliefs about saving money is less certain. Saving time has been, and continues to be, an important belief for most higher-income and many lower-income consumers, possibly because it relates to the “cost” side

of the cost–benefit framework, as opposed to beliefs relating to saving money or finding the product best that relate to the “benefit” side of the framework. It is possible that e-shoppers pay more attention to and act upon beliefs that are more immediate and tangible and at the start of the shopping episode, as opposed to others that are less tangible and are not realized till the end of the shopping process, if at all.

For higher-income online shoppers with more education, two different belief structures are discernible. One group appears to have beliefs that mainly relate to the time savings aspect of online shopping, while the other group has beliefs that relate to the ability to find hard-to-find products on the Internet. Neither group seems to focus on the money savings aspect of online shopping, possibly because they value their time and finding products that best match needs. Hence, the difference between the two groups relates to whether they focus on the cost of search (i.e., time spent) or a benefit of search (i.e., product fit obtained).

There appear to be three different belief structures among lower-income, less educated online shoppers, those who believe that online shopping saves time, those who believe it saves money or helps find products that best match needs, and those who believe it does neither. The group that believes that online shopping is neither about saving time or money, needs to be educated about both the time and money savings potential offered by online setting. It is possible that these consumers are late adopters of the Internet and have not yet developed the cyber fluency (i.e., Web expertise) needed to actively participate in e-commerce.

The group that believes that online shopping is about saving time may not be adequately distinguishing between potentially high-value and low-value online pursuits. Lower income consumers need to be educated that the Internet is not just about saving time, but also about saving money (Bertrand, Mullainathan, and Shafir 2006). They should be reminded of the importance of having separate “mental accounts” for high-value and low-value online activities and encouraged to use recommendation agents and shopbots to become knowledgeable about the online market place by using these tools to discover new products and update information on previously known products.

Manufacturers can play a more active role in changing the belief structures of lower-income, less educated consumers to include beliefs relating to both time and money savings potential of the Internet because they stand to benefit the most when all income segments begin to actively engage themselves in e-commerce. Economic models show that there is often a transfer of consumer surplus (i.e., the difference between the “price paid” and the “willing to pay” price) from consumers who purchase a high-priced product to those who buy a low-priced bargain in the same product category (Aron, Sundararajan, and Viswanathan 2006). Lower-income consumers stand to benefit the most from this transfer of consumer surplus because in a strange irony it has been created for them by their higher-income counterparts. For the public policy implications, the focus can be on designing communication strategies that can help lower-income consumers realize the same benefits of e-commerce as their higher-income

counterparts. These campaigns may be implemented by non-profit agencies such as the Ad Council (www.adcouncil.org). Maintaining and increasing the benefits from the Internet to all segments of society continues to be an important public policy goal (Scott Morton, Zettelmeyer, and Silva-Risso 2001).

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