Research Report – UCD-ITS-RR-11-30

The Impact of Product Type and Other Variables on Store and Internet Purchase Intentions: Clothing Versus Books

February 2011

Wei Tang
Patricia L. Mokhtarian

Institute of Transportation Studies ◦ University of California, Davis
One Shields Avenue ◦ Davis, California 95616
PHONE (530) 752-6548 ◦ FAX (530) 752-6572
www.its.ucdavis.edu

THE IMPACT OF PRODUCT TYPE AND OTHER VARIABLES ON STORE AND INTERNET PURCHASE INTENTIONS: CLOTHING VERSUS BOOKS

Wei Tang
Transportation Technology and Policy Program
and Institute of Transportation Studies
University of California, Davis
One Shields Avenue
Davis, CA, 95616, USA
laura5579@hotmail.com

and

Patricia L. Mokhtarian
Department of Civil and Environmental Engineering
and
Institute of Transportation Studies
University of California, Davis
Davis, CA 95616
voice: (530) 752-7062
fax: (530) 752-7872
e-mail: plmokhtarian@ucdavis.edu

February 2011

THE IMPACT OF PRODUCT TYPE AND OTHER VARIABLES ON STORE AND INTERNET PURCHASE INTENTIONS: CLOTHING VERSUS BOOKS

ABSTRACT

This study examines the effects of product type and channel-specific perceptions, among other variables, on store and internet purchase intentions. Using data collected from a web-based survey of two university towns in Northern California (N=903), we develop logistic regression models of purchase intention. The results demonstrate the contribution to purchase intention of product type and channel-specific shopping attitudes, in addition to previously-identified effects such as sociodemographics. The findings suggest that product type should be specified in future similar research, and that shopping channels in the choice set should be measured individually.

Key words: internet shopping, online shopping, store shopping, product type, logistic regression, attitudinal factors

ACKNOWLEDGEMENTS

Data collection was funded by the University of California Transportation Center; the present analysis is funded by the UC Davis Sustainable Transportation Center. The authors wish to thank Xinyu Cao, who participated heavily in the early stages of the survey design; Susan Handy, who provided helpful input on the survey design and administration; Tara Puzin, who collected and organized Census statistics on the study areas; and David Ory, who finalized the survey design, conducted the data collection and initial data cleaning activities, and performed the factor analysis on the general attitudes/personality traits/values.

1. Introduction

As an alternative to traditional store shopping, online shopping has shown a sturdy growth in the last decade. According to US Census Bureau data[1], internet-based retail sales in the US constituted about 1.1% of total retail sales[2] in 2001 and 2.0% of total retail sales in 2004. By 2007, online retail, at $126.7 billion, accounted for 3.2% of total retail sales. Online purchase shares of the two product types of particular interest to the present study are also increasing. Specifically, the percentage of all retail spending on *books, music, and videos* that took place online more than doubled in six years, from 7.7% in 2001 to 16.3% in 2007, while the online sales percentage for *apparel, accessories, footwear, and jewelry* quadrupled, from 1.6% in 2001 to 6.3% in 2007[3]. Online retail sales (excluding travel) are predicted to reach $267.8 billion in 2010, rising to $334.7 billion in 2012[4].

The rapid development of online shopping is creating more intensive behavioral change on the part of both retailers and customers, such as how, when and where consumers shop; where retailers should locate their stores; and how best to combine multiple retail channels for reaching customers. All those impacts will certainly influence transportation (particularly with respect to urban travel in terms of mode and frequency) to some extent, as well as future fuel consumption and air quality if the change in transportation demand is substantial. Thus, there is considerable value for transportation planners and researchers, in addition to marketing researchers and retailers, to better understand the nature of online shopping and the intensity of its adoption, particularly compared with traditional store shopping.

[1] Source: http://www.census.gov/compendia/statab/cats/wholesale_retail_trade/online_retail_sales.html (Table 1021), accessed January 2, 2010.
[2] Excluding food service.
[3] Table 1016, http://www.census.gov/compendia/statab/tables/09s1016.pdf, accessed July 13, 2009.
[4] Table 1015, http://www.census.gov/compendia/statab/tables/09s1015.pdf, accessed July 13, 2009.

The marketing research literature has a number of studies of e-shopping adoption or intention. This paper offers another contribution to the field, taking a binary purchase intention indicator (in-store versus online) as our dependent variable. Our study makes the following distinctive contributions:

- Most studies disregarded product type, and pooled all kinds of products together. This can yield vague or inconsistent results: it may overstate or understate consumers' e-shopping intention, because one or a few products they considered will be more or less suitable for e-shopping, and it may fail to identify explanatory variables that are important to some product types but not others. Our study explicitly considers two product categories: book (as a "search" good) and clothing (as an "experience" good) (see [19] for detailed explanations of these two types of goods).
- Most other studies only focused on modeling the purchase intention/possibility with respect to one shopping channel, namely the internet [1], or at best assessed one channel (internet) directly in comparison to another (store; [11]). In this study, we separately captured people's perceptions of internet and store. Although respondents will inevitably perceive one channel in the context of the characteristics of other available channels, asking their perceptions with respect to each channel individually gives a better indication of the perceived level of each characteristic. For example, if a respondent is just asked whether internet is "worse than", "similar to", or "better than" store on some characteristic and she says "similar to", we would not know whether she perceives the two channels as similarly bad or similarly good on that trait. Although only the difference matters to a discrete choice or intention, understanding individual channel perceptions is also of interest in its own right.

- We examined a rich set of explanatory variables in this analysis, including general shopping attitudes, channel-specific attitudes, shopping experience, internet usage and sociodemographics. Although subsets of most of these variables have been used in one or another study, the combined availability of all of them is virtually unique.

The remainder of the paper is organized as follows. The next section briefly reviews previous related research. The subsequent section describes data collection, survey contents and variables used in this study. We then introduce the methodology we used, followed by the presentation and interpretation of our logistic regression models of purchase intention. The last section summarizes the study and suggests future research directions.

2. Literature Review

A number of studies have analyzed e-shopping intention in the past decade [1, 3, 4, 8, 9, 12, 13, 15, 16, 17, 21, 24, 26, 28, 29]. A summary of some previous research is presented in Table 1. The table shows that many different methodologies have been used to conduct e-shopping intention research, such as discriminant analysis [21], analysis of variance (ANOVA) and t-tests [28], regression [4, 16], structural equation modeling (SEM) [8, 24], and binary logit modeling [13, 29].

[Table 1 goes about here]

As early as 1999, Van den Poel and Leunis used 93 responses to an electronic questionnaire, to explore the e-shopping propensity for 10 specified product categories (concert tickets, hotel reservations, car rental, software and newspapers, etc.) [28]. They conducted ANOVA and t-tests, focusing on the interaction effects of shopping channel with three “risk relievers” (i.e. price reduction, well-known brand and money-back guarantee); they found all “risk relievers” have positive effects on the propensity to choose e-shopping. This study made a pioneering contribution, but was limited by a small sample, a simple methodology, and having few explanatory variables.

In 2001, Liao and Cheung developed regression models of the willingness to e-shop, based on information obtained from 312 internet users in Singapore [16]. The variables they considered (“transaction security”, “price”, “shopping experience” and “network speed”) are quite similar to some of ours. However, our study includes more attitudinal factors and channel-specific ones. Choosing a different model (logistic regression) and analyzing data from a different country also distinguishes our study from theirs.

The work done by Van den Poel and Buckinx [29] brought us a new approach to modeling e-shopping intention. They mainly focused on “clickstream” variables, that is, data obtained purely by analyzing the stream of mouse clicks an individual makes while browsing the internet. They created clickstream variables at both the general level (such as “number of days since last visit”) and the detailed level (such as “total number of products viewed”), obtained from 1382 observations. Binary logit modeling was applied and substantial effects of clickstream variables on people’s e-shopping intention during the next visit were found.

Not surprisingly, factors related to e-shopping advantages such as speedy information-searching, perceived quality of e-vendors, ease of use, perceived trust and product offerings all show significantly positive impacts on e-shopping intention; variables reflecting computer knowledge, internet experience and e-shopping experience also show significantly positive influences. Other variables (e.g. transaction security risk, e-shopping transaction cost, performance uncertainty and behavioral uncertainty) have negative effects. Finally, as we expected, sociodemographic characteristics (e.g. income, education, gender) have strong influences on e-shopping behavior as well. However, none of those studies involve all of the elements that we incorporated (specifying product type, comparing different shopping channels and including channel-specific perceptions). Most of them considered shopping channel characteristics and consumer characteristics, but the product dimension was not considered by all of them. In addition, they modeled people's behavior based on either their attitudes with respect to e-shopping or the pros and cons of the e-shopping channel, without doing a cross-channel comparison and modeling the behavior as a choice among multiple available alternatives. Our study seeks to address these limitations.

3. Sampling Plan and Variables

3.1. Data collection

The data analyzed in this study were collected from an internet-based survey of northern California residents (see [20] for more details). The purpose of the study is to identify potential population segments and then to investigate e-shopping behavior for each segment by analyzing relationships among the measured variables, rather than to report descriptive statistics of the sample distributions and expect them to reflect the corresponding population. Accordingly, the representativeness of the sample is not our primary concern because the relationships of interest can be reliably measured even if the sample is not strictly representative [2, 7]. It is more important to have adequate variability on the dimensions of interest and "to have a substantial number of e-shopping occasions in the sample" [20, p. 3]. Nevertheless, it is certainly possible that the sample is biased in relevant ways. In addition to the sampling bias induced by the conscious choice of study locations as described below, a non-response bias may also limit the generalizability of the findings – especially the descriptive results, but potentially even the model-based relationships. For example, people who view the internet more favorably than average will be more likely to participate in an online survey, thereby exaggerating the perceived difference between store and internet on dimensions for which internet is generally superior, and diminishing the difference on dimensions for which store is generally superior.

To maximize the computer literacy and knowledge of e-shopping in the sample, two university communities were selected as study sites: Santa Clara and Davis. Both cities contain a large number of internet-literate residents, which helps to enrich the sample with a sizable portion of e-shopping adopters. One difference between the two neighborhoods is their regional locations: Santa Clara lies in the heavily urbanized Silicon Valley, while Davis is a smaller college town in the Sacramento metropolitan region.

Some 8,000 recruitment letters were mailed in June 2006 to randomly-selected households in those two cities. Approximately 6,500 letters apparently reached their intended addressee and around 1,000 respondents went to the website to complete the survey. In addition, 72 respondents requested and returned a paper version of the survey that was offered as an option. Overall, the response rate was 16%, which we considered quite good for an internet survey of this length (117 web pages; the paper version has 19 pages) and complexity. Typical response rates for mail-out/mail-back surveys of the general population are 10-40% [2]. We presume the higher end of that range to be unlikely for a survey as long as ours, with the additional barrier of being administered over the internet.

After eliminating surveys with incomplete responses on important questions and filling very small amounts of missing data with category-specific means, a working sample of 967 cases containing relatively complete data was established. Because the catalog channel was not well-represented in the sample, we focused this study on the individual's purchase intention between store and internet. Accordingly, we excluded 64 catalog-related cases and used the remaining 903 cases as our final working sample. The sample includes individuals who are retired (12.7%), homemakers (3.8%), and not currently working (3.5%), as well as those who work full time (60.5%) and part time (16.1%).

Table 2 presents sample statistics for the variables significant in the final model, together with a few additional characteristics. By design, the sample is fairly evenly distributed between the two product types studied here (where people are assigned to a category based on a recent purchase). People recently purchasing clothing were more likely to be female, while those purchasing in the book category were more likely to be male. The clothing subsample has more people in the relatively high annual household income categories than the book subsample does. Average age, average educational level, and home and work internet access are very similar between the book and clothing subsamples. Differences in the attitudinal factor scores are discussed when those variables are introduced in Section 3.2.2.

[Table 2 goes about here]

3.2. Variables

The survey started with a welcome question, followed by seven parts asking questions related to general and channel-specific shopping attitudes, previous general purchasing experience by channel and a specific recent purchase, shopping frequency for specific product types, respondents' usage of the internet, and sociodemographics. A more detailed description will be presented below.

As mentioned above, some portions of the survey focus on two product types – book/CD/DVD/videotape (a "search" good; henceforth "book") or clothing/shoes (an "experience" good; henceforth "clothing") – based "on the assumption (supported by other research) that relevant variables could be weighted differently depending on the nature of the product" [20, p. 18]. We chose these two relatively low-cost and frequently-purchased product categories to ensure the presence of sufficient recent purchase occasions in the sample (similar to the studies of [10] and [14]). Each respondent answered detailed questions with respect to a recent purchase of one of the two product types (the selected item was referred to as the "key item" or "key purchase"), which could have been purchased over the internet or in a store.

3.2.1. Dependent variable

Although the survey obtains information for a number of potential dependent variables of interest, this study analyzes people's intended shopping channel for a future purchase similar to the recent one for which the detailed information had just been obtained. The dependent variable is created from the survey question which asks "If you were going to make a similar purchase today, how would you do so?", with four possible response options: "In a store", "Over the internet", "Through a catalog" and "Other (please specify)". In the current study we concentrate on the first two channels: store and internet. As a result, our dependent variable is binary.

3.2.2. Explanatory variables

Based on the literature review and previous empirical studies, the explanatory variables obtained from the survey fall into five main categories, each described below.

General shopping-related attitudes: In survey Part A, the survey asked a series of 42 general shopping-related statements on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). Common factor analysis was used to extract the 13 (obliquely-rotated) factors (see [18] for the detailed results). Table 3 presents the strongly-loading statements for each factor. While some of these factors (e.g. impulse-buying, materialism, shopping enjoyment) could apply about equally well to either shopping channel (and were developed primarily for models of shopping frequency), we expect many of them (e.g. pro-technology, pro-environmental, caution, time consciousness, trustingness, pro-exercise and store enjoyment) to differentially affect individuals' shopping channel intentions.

[Table 3 goes about here]

Purchase experiences: In survey Part C, several questions related to the recent purchase were asked, such as how much money was spent, how the item was obtained, the purchase location, and the availability of alternative channels for that specific purchase. All these are possibly relevant explanatory variables giving important information on why the particular channel was adopted. Obviously, whether the experience is satisfying or not could play a very important role with respect to the next purchase intention.

Channel-specific attitudes: In survey Part D, respondents were asked to agree or disagree (on a five-point scale) with 28 channel-specific statements, assuming they were to make a purchase similar to the one discussed in Part C. To reduce the burden on the respondents, they were asked to complete such a set of statements for two of the three main shopping channels (store, internet, and catalog) – the channel chosen for the key purchase, and one alternative. Store was always assumed to be an alterative, so most (927) respondents completed the store-internet pair, with the remainder (40) reporting for store and catalog (38 for clothing and 2 for book). As mentioned earlier, these 40 cases, together with 24 whose future intention was either catalog or missing, were excluded from the present analysis, leaving 903 cases.

Common factor analysis was also conducted for this set of statements. The statements were pooled across channel and factor-analyzed to find eight underlying dimensions, as shown in Table 4. The final extracted factors will help us examine how attitudes differ by channel and product type. And they can serve as a useful complement to the general (Part A) shopping attitudes, allowing us to model e-shopping behavior from a more specific and concrete perspective. Channel-specific attitudes such as "post-purchase satisfaction", "cost savings", "convenience" and "enjoyment" are all likely to affect people's intention for a future similar purchase. Since, in a utility-maximizing discrete choice model such as ours, only differences in utility matter [27], these variables are represented in the model as differences between the store and internet scores on each factor.

[Table 4 goes about here]

Table 2 shows that, in general, the preference for one or a few shopping locations is higher with respect to physical stores than for internet sites, indicating (reasonably enough) that location efficiency or inertia is stronger in real space than in cyberspace. However, this difference is considerably larger for the clothing subsample than for the book subsample. On the other hand, in general the internet is seen as more convenient than store, but that convenience advantage is perceived to be much larger by the book group than the clothing group. Interestingly, the cost savings perception has opposite signs between the two groups: on average, book buyers consider the internet to be less expensive, while clothing buyers perceive the store to be less expensive (the same is true for the cost difference variable based on the recent purchase experience, shown in the final row of the table).

Use of internet and communication technology: In Part F, the survey asked some general questions about the respondents' usage of the internet, as well as other communication technologies. The information captured in this part reflects the individual's overall computer-use pattern, which can help to explain the propensity to choose the internet shopping channel in particular.

Sociodemographic characteristics: Part G of the survey captured an extensive list of sociodemographic variables such as gender, age, employment status (part time or full time), available work arrangements, and educational background, as well as household information such as household income, household size, number of clothing and book stores near home and work, and so on.

4. Methodology and Model Results

4.1. Methodology

Similar to some previous studies [23, 29], the logistic regression (LR) model (equivalent to binary logit) is used in this work. The purpose of the study is to model shopping channel intention for a future purchase. The main idea of the methodology is described as follows. As mentioned earlier, we hypothesize that variables might be weighted differently for different product types, so we first divided the data by product type, and then developed three separate models on the pooled data, the book subsample and the clothing subsample. Using the collective information indicated by those three models, we finally found a "best" hybrid model in which coefficients were either pooled or product-type-specific, as appropriate.

4.2. Model results and interpretations

4.2.1. The three separate LR models

Table 5 summarizes the three separate LR models, which are individually described below.

[Table 5 goes about here]

Pooled Model

In this model, 405 respondents intended to choose store for their next similar purchase and 285 favored internet shopping. The ρ^2 value [5] is 0.357, which is considered quite acceptable in the context of disaggregate discrete choice models. The 0.357 value is based on the equally-likely model, and since the market shares are not too unbalanced (58.7% and 41.3% for store and internet respectively), the market-share model (the model containing just the constant term) has a ρ^2 of just 0.022 (the focus of the survey on a recent internet purchase versus recent store purchase was manipulated somewhat to ensure the presence of a sizable number of internet purchases in the sample [20], and intention is highly correlated with choice. Thus, we effectively have a “choice-based sample”, and although, in such a case, all coefficients except the constant term are consistently estimated [5], the raw intention market shares are by no means representative). That means the main contribution to the model is from “true” variables (i.e. those other than the constant term), which is confirmed by the ρ^2 of 0.336 of the model re-estimated without the constant.

From the table, we see that shopping attitudinal factors and purchase experience variables play a key role in explaining the next purchase intention. They all show the expected signs. Four channel-specific perceptions (post-purchase satisfaction, efficiency/inertia, cost savings and convenience) are relevant to one’s purchase channel intention. Not surprisingly, the more positively store is perceived relative to the internet on these characteristics, the more likely store is to be the intended channel for the next purchase. However, it is interesting to note that four channel-specific perceptions are *not* significant in this model: product risk, financial/identity risk, enjoyment, and store brand independence. Although those perceptions are conceptually expected to be significant too, it is possible that their influence is partly reflected by the four perceptions that *do* appear. Each of the four perceptions not in the model has multiple significant (even if generally only around 0.1) correlations with the perceptions that *are* in the model. In particular, the enjoyment difference variable has correlations of 0.4 – 0.5 with three of the four significant channel-specific perceptions.

Two purchase experience variables (activeness of searching and context-specific cost difference) are significant in this pooled model. A higher value of the former variable means a respondent was more actively looking for the item on the purchase occasion. It has a negative sign (and is significant at the 93% level), meaning that the person who searched more actively for the previous purchase is more likely to intend to make the next similar purchase over the internet. Our interpretation is that such a person either learned or already knew the value of the internet for aiding a specific product search, and once using the internet to search, it is convenient to use it to purchase if the sought item is found there. Similarly, the context-specific cost difference variable also has a negative sign. A higher value of this variable indicates that store was perceived to be more expensive than internet for the specific purchase made recently. As a result, people with higher values are more likely to intend to use the more economical channel – internet – for their next purchase. In addition, a dummy variable for the book product type entered the model. As expected, it is more natural to purchase (and accordingly to intend to purchase) a book, as a "search" good, online compared to clothing, an "experience" good.

Finally, a sociodemographic trait – the binary variable for being female – is also significant in the model. Although its negative sign defies our expectation, it is also saying something meaningful. Originally, we expected women to be more likely than men to intend a store purchase, consistent with the image of men being more pro-technology, and enjoying store shopping less, than women. But in our sample, just looking at gender and intention, there is no significant difference in the distribution of intended channel between genders. So the fact that gender is significant in the model means that controlling for other variables is revealing a relationship that was hidden (suppressed) when only the two (i.e. gender and intention) were examined together. Specifically, gender explains an important component of the "residual" information in the intention variable after controlling for the other variables in the model.

It may be that we are trying to represent an essentially non-linear relationship as a linear one, and that some of the other variables (cost savings and convenience) are overemphasizing the influence of being female on store intentions (given that women have a significantly larger difference favoring store on those two variables than men do, with p-values of 0.000 and 0.028

for cost savings and convenience respectively). The female dummy variable seems to be partly correcting for that overemphasis. It may also be partly indicating a time pressure or impulse-buying effect (women are significantly more time conscious and impulse-buying than men in our sample): women, who tend to experience more time pressure than men [22], may be more inclined to shop over the internet to save time and/or to more readily indulge their impulsiveness. We tested whether the effect was stronger for women with young children; the interaction term did have a negative sign, but also a higher p-value (0.097) and the model had a somewhat lower goodness of fit. In addition, combined with the high correlation (0.76) between intention and adoption in our sample, our result is consistent with that of Bhatnagar et al. [6]: they found women to be more likely to adopt internet shopping, particularly for product categories such as books, music and CDs, and apparel and clothing. Finally, when we excluded the gender variable entirely, the ρ^2 dropped from 0.357 to 0.351. Although that is not a large drop, we decided to retain the gender variable because we believe that it is trying to tell us something useful. The sign is also quite robust: whenever the female binary variable appears in a model, it is with a negative sign.

Book model

In this model, 166 respondents intended to choose store for their next book purchase and 216 favored internet. The ρ^2 value is 0.363 and the market-share model has a ρ^2 of 0.012. The model re-estimated without the constant has a ρ^2 of 0.360. There are total of eight significant explanatory variables in the book model: five shopping attitudinal factors (trustingness, post-purchase satisfaction, cost savings, store brand independence and convenience), two purchase experience variables (activeness of searching and context-specific cost difference) and one internet usage variable (broadband internet accessibility at work).

Similarly to the pooled model, three channel-specific perceptions – post-purchase satisfaction, cost savings and convenience – have positive signs; the two purchase experience variables both have negative signs. The explanations are essentially the same as above.

Two other attitudinal factors are also significant in the book model: trustingness and store brand independence. The negative coefficient for trustingness means that those who are less trusting are more likely to intend to purchase in a store. This is the expected sign, since a tangible store can be more reassuring than a seemingly intangible internet retailer.

As shown in Table 4, high scores on the channel-specific store brand independence factors reflect people who are “always on the lookout for a new [store/internet site] to check out” (i.e. seek variety in their shopping locations), and/or who “prefer to shop at independent [stores/internet sites] rather than [those of] national chains” (perhaps to support small local businesses, or internet retailers with specialized goods or a particularly endearing character). The stronger this brand independence is for bricks-and-mortar stores compared to internet sites (i.e., the more positive the difference between store and internet scores on this factor), the more likely the individual is to intend to purchase in a store next time. This is an interesting finding, in view of the conventional wisdom that fostering retailer loyalty is desirable [25]. The implication is that people “locked in” to a certain internet site may (it stands to reason, though not directly shown by our results) be more likely to purchase from that site *if they purchase via the internet at all*, but may (our results suggest) be even more likely to purchase from stores, if they have a greater desire for independence there. Of course, the opposite can be true as well, for the shopper who is loyal (or captive) to a bricks-and-mortar store but brand-independent in cyberspace.

Finally, one variable in the internet usage category – broadband internet accessibility at work – appears in the model. The positive sign (indicating a higher intention to purchase in a store) seems counterintuitive because (particularly for book) we would expect ease of access to the internet to support intentions to buy online. However, we believe it may be a marker for individuals holding a largely sedentary desk job, who, to the extent they associate shopping with the work environment, would prefer store shopping (e.g. during the lunch hour) for exercise and a change of scenery.

Clothing model

Among the 310 cases included in this model, 239 respondents intended to choose store for their next clothing purchase and 71 favored internet. The ρ^2 value is 0.412. Since the market shares are unbalanced (77.1% and 22.9% intended store and internet respectively), the market-share model alone has a ρ^2 of 0.224. Re-estimating the final model without a constant term, however, yields a ρ^2 of 0.379, indicating that most of the explanatory power of the model lies in the "true" variables (i.e. they are helping to explain *why* the shares are unbalanced), not just the constant term. Five variables besides the constant are significant in the model: three channel-specific attitudinal factors (post-purchase satisfaction, efficiency/inertia and convenience), one purchase experience variable (context-specific cost difference) and the female indicator variable. These five variables all appear in the pooled model with the same signs, and have been discussed there.

4.2.2. The hybrid model including product-type-specific variables

The three models of Table 5 show that some variables appear important for both book and clothing product types, while others are product-type specific. Even among the former group, the weight given to a particular variable could differ by product type. At the same time, where variables are relevant to both product types, with similar weights, greater efficiency (smaller standard errors, meaning more precise estimates) can be attained by using the entire sample rather than smaller subsets to estimate the coefficients. Accordingly, it is worthwhile to develop a hybrid model in which coefficients are allowed to be product-type-specific or constant across product types, as appropriate. Using the collective information indicated by the previous three models, the "best" hybrid model we could find is presented in Table 6.

[Table 6 goes about here]

There are 690 cases included in the model, with 405 intending store and 285 intending internet. The ρ^2 value is 0.370 and the market-share model has a ρ^2 of 0.022. The 10 significant explanatory variables (excluding the constant) are: six shopping attitudinal factors (including one clothing-specific variable and two book-specific variables), two purchase experience variables, a binary variable for book product type and a clothing-specific binary variable for being female. All coefficients show the same signs as in the three separate models. The book-specific trustingness coefficient is of borderline significance (p=0.083), but we retain it for its conceptual contribution to the model. Based on a comparison of the separate book and clothing models we tested making some coefficients, such as the one for convenience, product-type-specific, but the outcomes were not statistically superior. Thus, all coefficients in the final model are either equal for both product types, or specific to only one of them.

The model displays some robustness with respect to the influence of product type, as well as some distinctions. Exactly half of the 10 significant variables are weighted equally across product: three channel-specific perception differences (post-purchase satisfaction, cost savings, and convenience), and the two experience variables (activeness of searching and context-specific cost difference). It is natural to expect these variables to have a similar impact on intention regardless of product type (of course, between the two types studied here). On the other hand, half of the variables are product-type-specific. Thus, having a higher level of trustingness, or more strongly preferring independent retailers in cyberspace than on the ground, leads to a stronger intention to purchase books online, but has no apparent effect on clothing purchase intentions. Conversely, having a stronger preference to concentrate one's activity at a few locations when it comes to online shopping compared to store shopping (i.e. having a more negative efficiency/inertia difference) leads to a stronger intention to purchase clothes online, but has no evident effect on book purchase intentions. Although these are not necessarily distinctions we would have predicted, and although their collective improvement to the model's goodness of fit is modest (informally judging by the difference in final log-likelihood functions of the pooled and hybrid models), they nonetheless justify our assumption that the same variables could weight differently for different products, and confirm the value of dividing products into different types for properly understanding online purchase behavior. One distinction that *is* unsurprising is that, all else equal, the book category has a stronger intention of being purchased online than does the clothing category.

5. Conclusions and Suggestions for Future Research

This study modeled shopping channel intention with respect to a future purchase of a book/CD/ DVD/videotape or clothing/shoes, for more than 900 residents of two university towns in northern California, with particular attention to the influences of product type and shopping attitudinal factors. In addition to previously-identified influences of internet usage, transaction cost and sociodemographics, we found that product type and comparative channel-specific perceptions play important roles in these models.

Both in the separate book and clothing models and in the final hybrid model, there is a certain degree of commonality of important variables. Post-purchase satisfaction, cost savings, convenience, activeness of searching, and context-specific cost difference have essentially equal coefficients for both product types, with the expected signs. The first three variables are differences in channel-specific perceptions between store and internet, so the greater that difference (in favor of store), the more strongly store is intended. The greater the activeness of searching for the most recent purchase, the more strongly internet is intended for a future similar purchase. And for the context-specific cost difference variable, a higher value indicates that store was perceived to be more expensive than internet for the specific purchase made recently, and is thus associated with a stronger intention to use the more economical internet channel on the next purchase.

Despite that commonality, there are also some differences between product types. The remaining five of the 10 variables significant in the final hybrid model are product-specific: three for book (dummy variable for book product type, trustingness and store brand independence) and two for clothing (efficiency/inertia and female dummy). These effects indicate the importance of distinguishing product type.

Half or more of the variables in each of the four models presented here are channel-specific perceptions. Although our binary dependent variable required only the differences between the store and internet channels as explanatory variables, many online shopping models have not even measured differences, but rather characteristics for online shopping alone. A few studies [11] measured characteristics of the internet relative to those of the store, but we are not aware of any others that measured characteristics of each channel separately, as we have done. Doing so would be critical to any multinomial context seeking to model choice or intention among more than two alternatives (such as including the catalog channel).

Only one of the 13 general shopping attitude factors shown in Table 3 (namely, trustingness) is significant in any of our models. Many of them were not expected to favor one channel over another, and most of those that *were* expected to impact channel intentions show significant (if generally modest) correlations with the channel-specific correlations that *do* appear in the models. In the strongest instance, the pro-technology factor has correlations of -0.14, -0.27, and -0.36 with post-purchase satisfaction, cost savings, and convenience, respectively. So it is reasonable to conclude that the influences of those variables are reflected in the channel-specific perception variables.

In summary, our findings indicate: (1) product type matters; we should not ignore it or blindly combine product type in choice or intention models; and (2) the perceived differences between store and internet shopping channels have significant impacts on people's purchase intention; changing the features of one channel will have crossover effects on the tendency to choose another channel. Therefore, to better understand people's intention or adoption, we should include multiple shopping channels considered to be salient by consumers, not just the one of main interest to the study.

Several directions for future research are indicated. Using the same data set, we plan to explore people's shopping channel adoption instead of future intention, and then compare the results to those obtained here, to identify variables significant to choice but not intention, and conversely. It would separately be valuable to create a new dependent variable reflecting the change (if any) between channel adoption and the successive intention, using multinomial logit or Markov models to investigate variables associated with changing. Finally, we will be developing latent class models of shopping intention, in which coefficients in the intention model are allowed to differ across endogenously-determined market segments.

For future data collection efforts, it would be highly desirable to include additional product categories (e.g. electronics, major appliances), to explore in greater detail how the channel-specific perceptions for these more expensive items might differ from those pertaining to the low-cost items studied here. Second, as mentioned in Section 2, the sampling and non-response biases of our sample limit confidence in the generalizability of the present results. Conducting a similar study on a larger, more representative sample would be instructive.

Finally, it would be valuable to conduct a repeated cross-sectional or panel study to examine how shopping behavior evolves over time with experience, technological improvements, and other factors. The present data were collected in 2006, and given the pace of technological advancement in this field, the question inevitably arises as to how stable the results found in this study will be. On the other hand, although the adoption of online shopping has continued to increase since these data were collected, the technology of the typical online shopping experience does not appear to have materially changed in the interim (for example, virtual reality technologies enabling shoppers to remotely feel fabrics or try on garments have not yet become commonplace, nor is it generally possible to filter the "universe" of prospective products beyond a few characteristics set by the retailer or comparison shopping website). So it can be argued that the data are still relevant to current conditions, and in any case they constitute a useful benchmark against which to measure future shifts in behavioral processes. Capturing those shifts with a panel dataset, paired with a dynamic structural equations approach to modeling perception and choice relationships, would be the ideal way to improve our understanding of the dynamic phenomenon of online shopping.

References

[1] T. Ahn, S. Ryu, I. Han, The impact of the online and offline features on the user acceptance of internet shopping malls, Electronic Commerce Research and Applications 3 (4), 2004, pp. 405-420.

[2] E. Babbie, The Practice of Social Research, 8th edition. Belmont, CA: Wadsworth Pub. Co., 1998.

[3] B. Bai, R. Law, I. Wen, The impact of website quality on customer satisfaction and purchase intentions: Evidence from Chinese online visitors, International Journal of Hospitality Management 27, 2008, pp. 391-402.

[4] F. Belanger, J.S. Hiller, W.J. Smith, Trustworthiness in electronic commerce: The role of privacy, security, and site attributes, Journal of Strategic Information Systems 11, 2002, pp. 245-270.

[5] M. Ben-Akiva, S.R. Lerman, Discrete Choice Analysis: Theory and Application to Travel Demand. Cambridge, Massachusetts: MIT Press, 1985.

[6] A. Bhatnagar, S. Misra, R.H. Rao, On risk, convenience and internet shopping behavior, Communications of the ACM 43 (11), 2000, pp. 98-105.

[7] D. Brownstone, Multiple imputation methodology for missing data, non-random response, and panel attrition. Chapter 18 in Tommy Garling, Thomas Laitila, and Kerstin Westin, eds, Theoretical Foundations of Travel Choice Modeling. Amsterdam: Elsevier, 1998, pp. 421-449. Available at http://www.its.uci.edu/its/publications/papers/ITS/UCI-ITS-WP-97-4.pdf.

[8] L. Chen, J. Tan, Technology adaptation in e-commerce: Key determinants of virtual stores acceptance, European Management Journal 22 (21), 2004, pp. 74-86.

[9] J. Choi, L.V. Geistfeld, A cross-cultural investigation of consumer e-shopping adoption, Journal of Economic Psychology 25 (6), 2004, pp. 821-838.

[10] M. Dijst, S. Farag, T. Schwanen, A comparative study of attitude theory and other theoretical models for understanding travel behaviour, Environment and Planning A 40, 2008, pp. 831-847.

[11] S. Farag, K.J. Krizek, M. Dijst, E-shopping and its relationship with in-store shopping: Empirical evidence from the Netherlands and the USA, Transport Reviews 26 (1), 2006, pp. 43-61.

[12] D. Gefen, D.W. Straub, Consumer trust in B2C e-commerce and the importance of social presence: Experiments in e-products and e-services, Omega 32, 2004, pp. 407-424.

[13] M.H. Hsiao, Shopping mode choice: Physical store shopping versus e-shopping, Transportation Research Part E 45, 2009, pp. 86-95.

[14] B. Jacobs, H.M. Klerk, Understanding female consumers' risks perception for apparel purchase on the internet, Journal of Family Ecology and Consumer Sciences 35, 2007, pp. 47-58.

[15] P. Lee, Behavioral model of online purchasers in e-commerce environment, Electronic Commerce Research 2, 2002, pp. 75-85.

[16] Z. Liao, M.T. Cheung, Internet-based e-shopping and consumer attitudes: An empirical study, Information & Management 38, 2001, pp. 299-306.

[17] H.D. McKnight, V. Choudhury, C. Kacmar, The impact of initial consumer trust on intentions to transact with a web site: A trust building model, Journal of Strategic Information Systems 11, 2002, pp. 297-323.

[18] P.L. Mokhtarian, D.T. Ory, X. Cao, Shopping-related attitudes: A factor and cluster analysis of northern California shoppers, Environment and Planning B 36 (2), 2009, pp. 204-228.

[19] P. Nelson, Information and consumer behavior, The Journal of Political Economy 78 (2), 1970, pp. 311-329.

[20] D.T. Ory, P.L. Mokhtarian, Description of a Northern California Shopping Survey Data Collection Effort. University of California, Davis, Institute of Transportation Studies, Research Report No. UCD-ITS-RR-07-03, March 2007, available at http://pubs.its.ucdavis.edu/publication_detail.php?id=1071.

[21] I. Phau, S.M. Poon, Factors influencing the types of products and services purchased over internet, Internet Research: Electronic Networking Applications and Policy 10 (2), 2000, pp. 102-113.

[22] L.C. Sayer, More work for mothers? Trends and gender differences in multitasking. Chapter 3 in Tanja van der Lippe and Pascale Peters, eds., Competing Claims in Work and Family Life. Cheltenham, UK: Edward Elgar, 2007, pp. 41-55.

[23] R. Shang, Y. Chen, L. Shen, Extrinsic versus intrinsic motivations for consumers to shop on-line, Information & Management 42, 2005, pp. 401-413.

[24] S. Shim, M.A. Eastlick, S.L. Lotz, P. Warrington, An online prepurchase intentions model: The role of intention to search, Journal of Retailing 77, 2001, pp. 397-416.

[25] S.S. Srinivasan, R. Anderson, K. Ponnavolu, Customer loyalty in e-commerce: An exploration of its antecedents and consequences, Journal of Retailing 78 (1), 2002, pp. 41-50.

[26] T.S.H. Teo, Y. Yu, Online buying behavior: A transaction cost economics perspective, Omega 33 (5), 2005, pp. 451-465.

[27] K. Train, Discrete Choice Methods with Simulation, 2nd ed. Cambridge, UK: Cambridge University Press, 2009.

[28] D. Van den Poel, J. Leunis, Consumer acceptance of the internet as a channel of distribution, Journal of Business Research 45, 1999, pp. 249-256.

[29] D. Van den Poel, W. Buckinx, Predicting online-purchasing behavior, European Journal of Operational Research 166 (2), 2005, pp. 557-575.

List of Tables

Table 1. Previous Research on E-shopping Intention Modeling

Reference	Methodology	Dependent variables	Explanatory variables (“+/-”: positive/negative relationship)
[28]	Analysis of variance (ANOVA) and t-test	Likelihood of e-shopping	Heavy internet users (+) Price reduction (+) Well-known brand (+) Money-back guarantee (+)
[21]	Discriminant analysis	E-shopping intention for 20 product and service categories	Products and services having low outlay (+) Having intangible value (+) Having high differentiation (+)
[16]	Regression	Willingness to e-shop	Perceived risks on transaction security (-) Education and IT training (+) Price (-) Perceived relative life content of e-shopping (-) Perceived quality of e-vendors (+) Level of internet usage (+)
[24]	Structural equation modeling (SEM)	E-shopping intention	Intention to use web for information search (+) Attitudes (+) Internet purchase experience (+) Perceived behavioral control (+, indirect)
[4]	Regression	E-shopping intention	Importance of privacy and security features (-) Site quality (+)
[8]	SEM	E-shopping intention	Perceived usefulness (+) Perceived trust (+, indirect) Compatibility (+, indirect) Perceived ease of use (+, indirect) Perceived service quality (+, indirect) Product offerings (+, indirect) Usability of storefront (+, indirect) Attitude toward using e-shopping (+)

[9]	SEM	E-shopping intention	Perceived risk (-, -) Perceived self-efficacy (+, +) Subjective norm (+, +)
[26]	SEM	Willingness to buy online	Transaction cost (-) Performance uncertainty (-, indirect) Behavioral uncertainty (-, indirect) Environmental uncertainty (-, indirect) Dependability (+, indirect) Online buying frequency (+, indirect)
[29]	Binary logit model	E-shopping adoption during the next visit	Number of days since last visit (+) Squared number of days since last visit (-) The average time per click in the session is lower than the average (-) Number of personal pages viewed during the last visit (-) Total number of products viewed (-) Male (+) Trust (+) Total number of purchases ever made at the site (+) Number of days between the visit and the last purchase (-)
[3]	SEM	Online purchase intention	Customer satisfaction (+) Website quality: functionality (+) Website quality: usability (+)
[13]	Binary logit model	E-shopping intention	Travel cost (-) Travel time (-) Delivery time (-) Male (-)

Table 2. Selected Characteristics of the Sample, by Product Type Subgroup

Characteristic (sample sizes)	**Pooled data N (%)**	**Book N (%)**	**Clothing N (%)**
Number of cases	903	450	453
Number of females	486 (54.1)	214 (48.0)	272 (60.2)
Average age (years) (881, 440, 441)	46.1	45.4	46.8
Average educational level [a] (903, 450, 453)	5.61	5.81	5.42
Annual household income (859, 433, 426)			
Less than $15,000	39 (4.3)	22 (4.9)	17 (3.8)
$15,000 to $29,999	59 (6.5)	29 (6.4)	30 (6.6)
$30,000 to $49,999	114 (12.6)	61 (13.6)	53 (11.7)
$50,000 to $74,999	189 (20.9)	100 (22.2)	89 (19.6)
$75,000 to $124,999	274 (30.3)	129 (28.7)	145 (32.0)
$125,000 or more	184 (20.4)	92 (20.4)	92 (20.3)
Home internet access [b] (902, 450, 452)			
Low speed	185 (20.5)	92 (20.4)	93 (20.5)
Broadband	730 (80.8)	366 (81.3)	364 (80.4)
Work internet access [b] (889, 446, 443)			
Low speed	41 (4.6)	20 (4.5)	21 (4.7)
Broadband	700 (78.7)	366 (82.1)	334 (75.4)
	Mean (s.d.)	**Mean (s.d.)**	**Mean (s.d.)**
Shopping attitudinal factors			
Trustingness	-0.014 (0.751)	-0.034 (0.778)	0.005 (0.722)
Post-purchase satisfaction [c]	0.921 (1.688)	0.825 (1.745)	1.016 (1.626)
Efficiency and inertia [c]	0.716 (1.607)	0.263 (1.564)	1.166 (1.523)
Cost savings [c]	-0.378 (2.085)	-1.153 (1.921)	0.393 (1.953)
Store brand independence [c]	0.587 (1.570)	0.801 (1.557)	0.374 (1.556)
Convenience [c]	-1.118 (1.602)	-1.589 (1.582)	-0.651 (1.481)
Purchase experiences			
Activeness of searching [d]	2.576 (0.699)	2.660 (0.670)	2.500 (0.718)
Context-specific cost difference [e]	-0.072 (0.739)	0.130 (0.731)	-0.320 (0.672)

[a] 1=Some grade school or high school; 2=High school diploma or equivalent; 3=Some college or technical school; 4=Two year college associates degree; 5=Four year college/technical school degree; 6=Some graduate school; 7=Completed graduate degree(s).
[b] Categories are not mutually exclusive.
[c] Difference between channel-specific perceptions: store factor score minus internet factor score.
[d] 1=I had not previously thought about buying such an item – I just came across it; 2=I had previously thought about buying such an item if I found it, but I was not actively looking for it on this occasion; 3=I was actively looking for such an item on this occasion.
[e] A qualitative measure of the perceived cost difference between store and internet with respect to the recent purchase; a higher value means the store channel costs more (-1=store is cheaper; 0=about the same price; 1=store is more expensive).

Table 3. General Attitudes/Personality Traits/Values Factors

Factor	Survey Statement	Loading
Pro-credit card	Credit cards encourage unnecessary spending.	-0.573
	I prefer to pay for things by cash rather than credit card.	-0.514
Pro-environ-mental	We should raise the price of gasoline to reduce congestion and air pollution.	0.605
	To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.556
	Shopping travel creates only a negligible amount of pollution.	-0.447
	A lot of product packaging is wasteful.	0.388
	Whenever possible, I prefer to walk or bike rather than drive.	0.354
Pro-exercise	I follow a regular physical exercise routine.	0.562
	Whenever possible, I prefer to walk or bike rather than drive.	0.540
Impulse buying	I generally stick to my shopping lists.	-0.586
	When it comes to buying things, I'm pretty spontaneous.	0.565
	I like a routine.	-0.289
	If I got a lot of money unexpectedly, I would probably spend more of it than I saved.	0.273
Caution	"Better safe than sorry" describes my decision-making style.	0.634
	Taking risks fits my personality.	-0.509
	I like a routine.	0.319
	I am generally cautious about accepting new ideas.	0.316
	I prefer to see other people using new products before I consider getting them myself.	0.265
Materialism	For me, a lot of the fun of having something nice is showing it off.	0.604
	I would/do enjoy having a lot of expensive things.	0.495
	Buying things cheers me up.	0.363
	My lifestyle is relatively simple, in terms of material goods.	-0.302
Price conscious-ness	It's too much trouble to find or take advantage of sales and special offers.	-0.648
	It's important to me to get the lowest prices when I buy things.	0.604
Time conscious-ness	I'm often in a hurry to be somewhere else when I'm shopping.	0.580
	I'm too busy to shop as often or as long as I'd like.	0.425
Trendsetting	I often introduce new trends to my friends.	0.604
	I like to track the development of new technology.	0.392
Trustingness	People are generally trustworthy.	0.469
	I tend to be cautious with strangers.	-0.408
	I enjoy the social interactions shopping provides.	0.343

Store enjoyment	Even if I don't end up buying anything, I still enjoy going to stores and browsing.	0.769
	I like to stroll through shopping areas.	0.752
	Shopping helps me relax.	0.586
	Shopping is fun.	0.529
	For me, shopping is sometimes an excuse to get out of the house or workplace.	0.427
	Shopping is usually a chore for me.	-0.389
	Buying things cheers me up.	0.293
	Shopping is too physically tiring to be enjoyable.	-0.285
Shopping enjoyment	Shopping is too physically tiring to be enjoyable.	-0.440
	Shopping is usually a chore for me.	-0.408
	My lifestyle is relatively simple, in terms of material goods.	-0.309
	"Variety is the spice of life".	-0.267
Pro-technology	Computers are more frustrating than they are fun.	-0.735
	The internet makes my life more interesting.	0.582
	I like to track the development of new technology.	0.478
	Technology brings at least as many problems as it does solutions.	-0.444

Notes: Adapted from [18]. Based on oblimin rotation of the principal axis factoring (common factor analysis) solution. Loadings greater than 0.25 in magnitude displayed.

Table 4. Channel-specific Perceptual Factors

Factor	Survey statement (clothing – store version)	Loading
Conven-ience	When it comes to buying clothing/shoes, I can find anything I want in stores.	0.640
	A lot of times, products I want are unavailable in stores.	-0.636
	The product information I need is easy to find in stores.	0.615
	Stores are open whenever I want to shop.	0.518
	When shopping in stores, it is easy to check the availability of products.	0.475
	The stores I want/need to shop at are conveniently located.	0.447
	All things considered, buying in stores saves me time.	0.413
	I often find shopping in stores to be frustrating.	-0.345
Product risk	I'm concerned that a product I purchase in a store will not perform as expected (e.g. quality, etc.).	0.469
	When shopping in stores, I am able to experience products before buying, to the extent that I want to.	-0.374
	I am concerned that unfamiliar stores will fail to meet my expectations.	0.334
Enjoy-ment	Shopping in stores is boring.	-0.768
	I enjoy shopping in stores.	0.760
	I often find shopping in stores to be frustrating.	-0.407
	With respect to buying clothes/shoes, I am always on the lookout for a new store to check out.	0.323
Financial/ identity risk	It is risky to release credit card information to stores.	0.838
	I am uncomfortable about providing personal information to stores.	0.627
Efficiency /inertia	I value stores that allow me to fulfill many of my shopping needs in just one location.	0.449
	When it comes to clothing/shoes, I have a strong preference for shopping at one or a few particular stores.	0.414
	When shopping in stores, I am able to experience products before buying, to the extent that I want to.	0.322
Cost-saving	All things considered, buying in stores saves me money.	0.760
	Considering taxes and other costs, clothes/shoes are usually more expensive when purchased in stores.	-0.753
Store brand indepen-dence	I prefer to shop at independent stores rather than national chains.	0.561
	With respect to buying clothes/shoes, I am always on the lookout for a new store to check out.	0.389
Post-purchase satis-faction	I often have to wait too long for a store to obtain the product I want to purchase.	-0.594
	Stores typically provide poor after-purchase customer service.	-0.559
	If necessary, it is easy to return a product purchased at a store.	0.486
	When shopping in stores, I am able to immediately obtain the products I purchase.	0.412
	It is difficult to compare products at stores.	-0.316

Notes: Based on oblimin rotation of the principal axis factoring (common factor analysis) solution. Pattern matrix loadings greater than 0.30 in magnitude are displayed.

Table 5. Logistic Regression Model of Intended Next-Purchase Channel for Pooled, Book and Clothing Data (1 = Store, 0 = Internet)

Variable Name	Model 1: pooled data		Model 2: book data		Model 3: clothing data	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	1.956	.000	.702	.260	1.188	.000
Shopping attitudinal factors						
Trustingness			-.359	.051		
Post-purchase satisfaction [a]	.399	.000	.342	.000	.446	.000
Efficiency and inertia [a]	.191	.008			.305	.008
Cost savings [a]	.172	.012	.259	.005		
Store brand independence [a]			.335	.001		
Convenience [a]	.379	.000	.511	.000	.340	.010
Purchase experiences						
Activeness of searching [b]	-.273	.069	-.425	.037		
Context-specific cost difference [c]	-1.127	.000	-1.258	.000	-1.209	.000
Internet usage						
Broadband internet accessibility at work			.770	.049		
Sociodemographics						
Female	-.482	.023			-.675	.048
Product type						
Dummy variable for book	-.884	.000				
Valid number of cases, N	690 (S: 405; I: 285) [d]		382 (S: 166; I: 216) [d]		310 (S: 239; I: 71) [d]	
Final log-likelihood, LL($\boldsymbol{\beta}$)	-307.520		-168.712		-126.433	
Log-likelihood for market share model, LL(MS)	-467.784		-261.501		-166.812	
Log–likelihood for equally-likely (EL) model, LL(0)	-478.272		-264.782		-214.876	
No. of explanatory variables, K (including constant)	9		9		6	
$\rho^2_{ELbase} = 1 - \mathrm{LL}(\boldsymbol{\beta}) / \mathrm{LL}(0)$	0.357		0.363		0.412	
Adjusted $\rho^2_{ELbase} = 1 - [\mathrm{LL}(\boldsymbol{\beta}) - K] / \mathrm{LL}(0)$	0.338		0.329		0.384	
χ^2 (between final model and the EL model)	341.503		192.141		176.886	
χ^2 (between the final model and the MS model)	320.526		185.577		80.759	

[a] Difference between the store-specific and internet-specific factor scores.
[b] See Table 2 for definition.
[c] See Table 2 for definition.
[d] S and I represent store and internet respectively.

Table 6. Logistic Regression Hybrid Model Result (1 = Store, 0 = Internet)

Variable Name	**Hybrid model**	
	Coefficient	P-value
Constant	2.149	.000
Shopping attitudinal factors		
Trustingness (book-specific)	-.305	.083
Post-purchase satisfaction [a]	.381	.000
Efficiency and inertia (clothing-specific) [a]	.301	.009
Cost savings [a]	.183	.008
Store brand independence (book-specific) [a]	.292	.002
Convenience [a]	.378	.000
Purchase experiences		
Activeness of searching [b]	-.293	.054
Context-specific cost difference [c]	-1.176	.000
Sociodemographics		
Female (clothing-specific)	-.851	.013
Dummy variables or interaction terms		
Dummy variable for book	-1.419	.000
Valid number of cases, N		690 (S: 405; I: 285) [d]
Final log-likelihood, LL(β)		-301.330
Log-likelihood for market share model, LL(MS)		-467.784
Log–likelihood for equally-likely (EL) model, LL(0)		-478.272
No. of explanatory variables, K (including constant)		11
ρ^2_{ELbase} = 1– LL(β) / LL(0)		0.370
Adjusted ρ^2_{ELbase} = 1– [LL(β) – K] / LL(0)		0.347
χ^2 (between final model and the EL model)		353.883
χ^2 (between the final model and the MS model)		332.907

[a] Difference between the store-specific and internet-specific factor scores.
[b] See Table 2 for definition.
[c] See Table 2 for definition.
[d] S and I represent store and internet respectively.