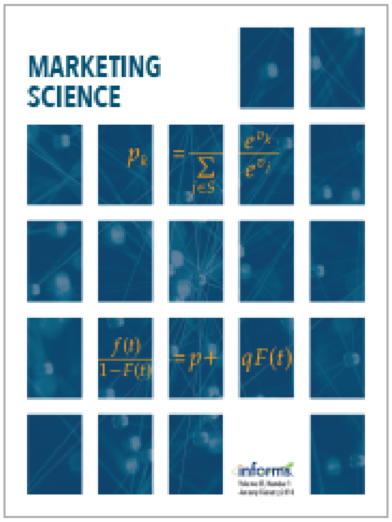

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Usage Experience with Decision Aids and Evolution of Online Purchase Behavior

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This study investigates how prior usage experience with various decision aids available in an Internet shopping environment contributes to online purchase behavior evolution. Four types of decision aids are examined: those for (1) nutritional needs, (2) brand preference, (3) economic needs, and (4) personalized shopping lists. We construct and estimate nonhomogeneous hidden Markov models of store- and category-level purchase decisions, in which parameters vary over time across hidden states as driven by usage experience with different decision aids. We find that consumers evolve through distinct behavioral states over time, and the evolution is attributable to their prior usage experience with various decision aids. Moreover, the impact varies by the specific decision aid, behavioral state, and category characteristics. In addition, consumers gravitate toward habitual decision processes in online grocery stores, and their average price and promotion sensitivities increase first and then decrease but the level of heterogeneity rises continuously. We identify beneficial versus potentially undesirable decision aids and demonstrate how the proposed research method can help online retailers improve their store environments, design customized promotions, and quantify the payoffs of these strategies.

Keywords: Internet marketing; shopper marketing; interactive decision aids; customized promotions; store environment; retail management; e-commerce; decision heuristics; click-stream data; Bayesian statistics; hidden Markov model

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1. Introduction

Internet retailing has experienced explosive growth for over a decade. As more shoppers begin to make purchases online, it is important to understand how they adapt to this increasingly prominent retail channel and whether their purchase behavior evolves as they gain more experience with the new shopping environment. Prior research has examined the impact of the Internet environment on purchase decision processes (e.g., Bechwati and Xia 2003, Häubl and Trifts 2000, Hollander and Rassuli 1999, Lee and Geistfeld 1998) and the differences between online and offline purchase behaviors (e.g., Danaher et al. 2003, Degeratu et al. 2000, Zhang and Wedel 2009). What is lacking in the literature is a comprehensive examination of the patterns of purchase behavior evolution in online stores, and more importantly, what may drive these behavior changes over time.

It is well documented that the store environment can influence a consumer's decision-making process (e.g., Inman et al. 2009, Park et al. 1989). A unique feature of the Internet shopping environment is the ability to offer a variety of interactive decision aids that can facilitate consumers' shopping processes. For example, many online retailers provide decision aids that allow shoppers to sort alternatives or filter them with certain criteria, to create personalized shopping lists, or to retrieve previous order lists. Studies have shown that such interactive decision aids can influence consumers' information search processes, purchase outcomes, and satisfaction (e.g., Bechwati and Xia 2003, Häubl and Trifts 2000, Hollander and Rassuli 1999, Lee and Geistfeld 1998). Therefore, one can speculate that, as online shoppers accumulate more experience with using various decision aids, their purchase behavior may also change over time as a consequence. In addition, their decision-making processes may evolve to patterns distinctly different from those in brick-and-mortar store environments. Research on shopper marketing shows that most purchases made in brick-and-mortar stores involve in-store decision making, as the numerous sensory stimuli in a store often trigger unrecognized or forgotten needs (Inman et al. 2009, Park et al. 1989). In contrast, there are few sensory stimuli in online stores. Our study will shed light on how consumer decision-making processes may evolve over time in online stores and how they may differ from those in the brick-and-mortar shopping environment.

The main objective of this study is to conduct an empirical investigation on whether and how usage experience with various decision aids available in Internet stores may drive the evolution of online purchase behavior, and what roles different types of decision aids may play in the process. Our data are provided by a leading Internet grocery retailer that was among the very first to sell groceries online. The data set was collected during the period when the retailer first launched its web-based operation, which makes it particularly appealing to study the evolution of online purchase behavior. It includes detailed click-stream navigation information as well as household purchase history data in multiple product categories, and thus allows us to identify the patterns of decision aid usage and to link it to household purchase behavior.

We construct a nonhomogeneous hidden Markov model (NHMM) of consumers' store visit and shopping trip spending decisions in the online store, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids. The hidden Markov model is well suited for the purposes of studying purchase behavior evolution. To validate findings from the store-level model and to explore the differences across categories, we also estimate the proposed model for eight product categories.

We address the following managerial questions in this study: (1) How do consumers' purchase tendency and price and promotion sensitivities evolve over time as they learn and adapt to a new online store? (2) How does their usage experience with different decision aids affect the behavior evolution? Specifically, what types of decision aids may enhance consumers' loyalty to an online store, and what types of decision aids may mitigate price competition? (3) Are there any differences in the patterns across product categories? (4) How to design targeted promotion activities in an online store based on the proposed model and how to quantify the expected sales improvement from these actions.

Our empirical investigation is carried out in the context of online grocery stores. After initial struggles and some high profile failures, online grocery retailing has shown a resilient comeback and experienced steady growth in recent years. According to a recent report by the Nielsen Company, online grocery retailing has grown at a more than 20% compound annual rate since 2003 (Swedowsky 2009). Forrester Research estimates that online grocery sales have reached $14.5 billion in 2013 (Rudarakanchana 2014), and 14% of U.S. households have purchased groceries online (Hartman Group 2013). Findings from our study will be relevant to a wide range of companies, especially as many powerful brick-and-mortar retailers (e.g., Safeway, Albertsons, and Walmart) as well as Internet retailers (e.g., Amazon.com) venture into the online grocery retailing business.

The key contributions of this study are the following: (1) By utilizing a unique data set and employing sophisticated modeling techniques, it reveals how store- and category-level baseline purchase tendencies and price and promotion sensitivities evolved over time as consumers adapted to a new online shopping environment. Our model enables online retailers to infer each individual customer's purchase behavior at a given time and to use that as a basis for designing various customization strategies. (2) It reveals how consumers' purchase behavior evolution in an online store was influenced by their prior usage experience with various decision aids. We identify those decisions aids that can help online retailers enhance store loyalty and mitigate the pressure of price and promotion competitions, and caution them of other decision aids that could yield undesirable consequences. Such insights can help retailers substantially improve the designs and operations of their online stores. (3) We provide specific decision recommendations to online retailers on how to design customized promotion offerings by tracking consumers' decision aid usage patterns, and our model enables them to quantify the expected payoffs of these strategies. (4) We examine cross-category similarities and differences in the impact of decision aid usage experience on purchase behavior evolution, which provides valuable insights to online retailers on how to prioritize various merchandising activities across categories. (5) It reveals toward what types of decision aids consumers tended to gravitate in online grocery stores and provides an interesting contrast with previous findings on decision making in offline shopping environments.

2. Conceptual Development and Literature Review

2.1. Online Decision Aids and Decision Heuristics

The behavior research literature provides an abundance of evidence showing that consumers employ a variety of heuristics to help them make decisions in a relatively quick and effortless fashion (e.g., Broniarczyk and Alba 1994, Goldstein and Gigerenzer 2002, Hoyer 1984). Decision aids available in online stores can assist consumers in utilizing a variety of decision heuristics. In this section, we first describe and classify four types of decision aids that are commonly available in present-day online grocery stores, and then link them to plausible underlying decision heuristics.

1. *Decision aids for nutritional needs*. Some online grocery retailers provide decision aids to facilitate easy access and usage of nutritional information to compare products. These decision aids include sorting functions (e.g., by calories, cholesterol, sugar, or fat)

and screening functions (e.g., "organic only," "kosher only") to rank, compare, or filter the available alternatives with certain nutritional criteria. For example, http://www.groceryexpress.com offers 12 functions to assist consumers' nutritional needs, and http://www.freshdirect.com provides 16 such functions.

2. *Decision aids for brand preference*. In online stores, consumers can choose their preferred products by the brand name using functions such as sorting by brand or search by brand name. This type of decision aids is ubiquitous in online stores (e.g., http://www.freshdirect.com, http://www.netgrocer.com, and http://www.walmart.com). Compared to brick-and-mortar stores, they make the shopping process particularly efficient for consumers who have strong brand preferences by avoiding effortful navigations across physical shelves.

3. *Decision aids for economic needs*. Online decision aids such as "sorting by price," "sorting by promotion," or "club special first" (see http://www.freshdirect.com, http://www.safeway.com, http://www.peapod.com for examples) make the shopping process easier for consumers who are sensitive to price differences or are looking for special deals.

4. *Personalized shopping lists*. Some online stores offer consumers the option to create personal shopping lists (e.g., http://www.harristeeter.com, http://www.peapod.com) or automatically save their previous order lists (e.g., http://www.peapod.com, http://www.freshdirect.com, and http://www.safeway.com). They allow consumers to complete the shopping process quickly without having to engage in careful evaluation of individual items.

Although the specific context of our study is online grocery stores, most of the decision aids classified above, with the exception of those for nutritional needs, apply to other types of retailers and product categories.

Ratchford's (1982) cost-benefit model for choice and information seeking behavior postulates that consumers trade off the costs and benefits of obtaining additional information in their choice decisions. It has been shown that they engage in additional search only when the perceived benefits exceed the perceived costs (Moorthy et al. 1997). Based on this theory, we conjecture that consumers only search for information that they will use for a given decision task, although our data do not allow us to pinpoint the underlying decision heuristics. The usage of a decision aid for nutritional needs or brand preference would indicate that a consumer has evaluated (at least some of) the choice alternatives based on their nutritional attributes or brand information, and the usage of decision aids for economic needs would indicate that price and/or promotion information has played a role in the decision process. Therefore, the usage of each of the first three types of decision aids would indicate that a consumer has engaged in on-the-spot information search before reaching the final decision.

The fourth type of decision aid, personalized shopping lists, enables consumers to make purchase decisions based on their previous purchases or from a preconstructed list without having to make on-the-spot information search and evaluation. Shopping lists can serve as a memory aid (Block and Morwitz 1999). Inman and colleagues (2009) show that consumers who use shopping lists tend to make fewer unplanned purchases. The usage of this type of decision aid would indicate a habitual decision process, similar to the "choosing by default" heuristic (Frederick 2002). We leave it as an empirical question with regard to whether consumers tend to engage in on-the-spot or habitual decision processes in online stores, where decision aids facilitating both types of decision processes are easily accessible.

2.2. Usage Experience with Decision Aids and Evolution of Online Purchase Behavior

We focus on two important aspects of purchase behavior in this study: consumers' tendency to purchase from an online store and their price and promotion sensitivities. We now discuss how usage experience with various decision aids provided by an online store may differentially influence consumers' purchase behavior evolution in the store.

We conjecture that usage experience with those decision aids that can create a "lock-in" effect, such as personalized shopping lists, would also increase a consumer's tendency to shop from the focal store. Since these shopping lists are stored in a particular online store, a consumer who is accustomed to using these lists in one store would face higher switching costs of moving to other (online or offline) stores. In addition, if an online store offers decision aids that allow consumers to easily access and compare product attributes, usage experience with this type of decision aids would reinforce the unique advantages offered by the store, and thus is likely to increase her loyalty to the store, especially if the store choice competition is between an online store and brick-and-mortar stores.

Prior usage experience with online decision aids may also affect consumers' price and promotion sensitivities, and the effects are likely to vary by the type of decision aids. As discussed previously, personalized shopping lists allow consumers to use the least effortful decision heuristic without having to search or evaluate any product information on the spot, including pricing or deal information. This implies that, the more frequently a consumer has used personalized shopping lists in the past, the less salient pricing or deal information is in her mind, and thus usage experience with this type of decision aid is expected to reduce her price and promotion sensitivities. In contrast, prior usage experience with decision aids for economic needs can increase the salience of price and deal information and reinforce the economic benefit of such search effort, and therefore can strengthen a consumer's price and promotion sensitivities.

In brick-and-mortar stores, consumers are more likely to focus on price- or deal-related information because it is easily available and highly salient with frequent feature and display advertisements (Degeratu et al. 2000). In contrast, interactive decisions aids available in online stores allow consumers to more efficiently access and utilize information about other product attributes. This suggests that, at least for some consumers, the weight of price information is likely to diminish and the importance of other attribute information is likely to increase (Degeratu et al. 2000, Smith et al. 2000), and thus their price and promotion sensitivities may decrease over time in online stores. On the other hand, decision aids intended for economic needs make it easier for value-conscious consumers to use price- or deal-related information. Therefore, it is also possible that these consumers' price and promotion sensitivities will increase over time in online stores. The possibility of both types of consumers imply that there is likely a divergence of price and promotion sensitivities over time as consumers gain more experience in an online shopping environment.

3. Model Formulation

This study investigates whether and how the usage experience with various online decision aids may affect consumers' purchase behavior evolution over time. We construct nonhomogeneous hidden Markov models to study store-level and category-level purchase behaviors, respectively, where the former captures store visit and shopping trip spending decisions, and the latter captures category purchase incidence and purchase quantity decisions. We adopt a type II Tobit model to jointly model the two decisions at the store/category level. In each model, parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids. Our model belongs to the family of NHMMs, because the transition probabilities are formulated as functions of time-varying covariates. To conserve space, we only describe the formulation of the store-level model.

3.1. A Type-II Tobit Model of Store Visit Incidence and Shopping Trip Spending

3.1.1. Store Visit Incidence. Let U_{it} = household i's latent utility of purchasing from the online store in week t; $I_{it} = 1$ if household i makes a purchase from the online store in week t, 0 otherwise. Without losing generality, we can scale U_{it} such that $I_{it} = 1$ if $U_{it} > 0$ and 0 otherwise. The store visit utility function is specified as

$$U_{it} = \beta^s X_t + \varepsilon_{it}, \quad \text{where } \varepsilon_{it} \sim N(0, \delta_s^2), \qquad (1)$$

where X_t is a vector of marketing mix variables in the online store in week t, and β^s is a vector of their coefficients (including the intercept) given that a household is in hidden state s. The intercept can be interpreted as a household's baseline tendency to purchase from the store or store loyalty in a given state. We choose to focus on regular price and price cut for the marketing mix component in our empirical analysis, because price and promotion sensitivities are key aspects of purchase behavior that we are interested to study here. To uniquely identify the hidden states, we constrain the intercepts across states in Equation (1) to be in an ascending order. We also set $\delta_s^2 = 1$ for identification purposes.

3.1.2. Shopping Trip Spending. Shopping trip spending is observed only when a household makes a purchase from the online store. We denote Q_{it}^* as household i's latent shopping trip spending amount in the online store in week t, and Q_{it} as the household's observed spending amount in week t. Then, $Q_{it} = Q_{it}^*$ if $I_{it} = 1$ and 0 otherwise. We specify Q_{it}^* as

$$Q_{it}^* = \phi^s Z_t + \upsilon_{it}, \quad \text{where } \upsilon_{it} \sim N(0, \sigma_s^2), \qquad (2)$$

where Z_t is a vector of marketing mix variables in the online store in week t (regular price and price discount in the empirical analyses), and ϕ^s is a vector of their coefficients (including the intercept) given that a household is in hidden state s. Since shopping trip spending (in dollars) data are skewed, we work with its logarithm transformation in the empirical analysis.

We take into account the interdependence of store visit and shopping trip spending decisions by assuming that the error terms in Equations (1) and (2), ε_{it}, and υ_{it} follow a bivariate normal distribution with zero means and the covariance matrix Σ:

$$\begin{pmatrix} \upsilon_{it} \\ \varepsilon_{it} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_s^2 & \rho_s \sigma_s \\ \rho_s \sigma_s & 1 \end{pmatrix} \right). \qquad (3)$$

3.2. Hidden States and Transition Probabilities

We model the evolution of the hidden-state-specific parameter vectors β^s and ϕ^s in the Tobit model according to a Markov transition matrix P_{it}, the elements of which are specified as functions of usage experience with various decision aids. In our model, consumers are allowed to switch back and forth between the hidden states. We specify the probabilities of switching from hidden state S_{t-1} in week $t-1$ to hidden state S_t in week t for household i in a K-state NHMM using the ordered logit formulation (see Netzer et al. 2008, p. 190):

$$\begin{aligned}
P_{it}(S_t=1\mid S_{t-1},D_{it}) &= \frac{\exp(\lambda_{i1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})}{1+\exp(\lambda_{i1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})},\\
P_{it}(S_t=2\mid S_{t-1},D_{it}) &= \frac{\exp(\lambda_{i2,S_{t-1}}-\gamma_{s_{t-1}}D_{it})}{1+\exp(\lambda_{i2,S_{t-1}}-\gamma_{s_{t-1}}D_{it})}\\
&\quad -\frac{\exp(\lambda_{i1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})}{1+\exp(\lambda_{i1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})},\\
&\cdots\\
P_{it}(S_t=K\mid S_{t-1},D_{it}) &= 1-\frac{\exp(\lambda_{iK-1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})}{1+\exp(\lambda_{iK-1,S_{t-1}}-\gamma_{s_{t-1}}D_{it})},
\end{aligned}\tag{4}$$

where K is the number of hidden states. Parameters $\lambda_{i1,s_{t-1}}, \lambda_{i2,s_{t-1}}, \ldots, \lambda_{iK-1,s_{t-1}}$ are household i's state-specific cut-off points and their values are set in ascending order for a given $S_{t-1} \in \{1, 2, \ldots, K\}$. The vector D_{it} represents household i's usage experience variables for a set of decision aids, and $\gamma_{s_{t-1}}$ is a vector of their state-specific coefficients. In the empirical analysis, we categorize and examine six types of decision aids, including one for nutritional needs, one for brand preference, two for economic needs, and two for personalized shopping lists. Thus the vector D_{it} includes cumulative usage experience measures of these six decision aids. We also include two other variables about decision aid usage patterns: "*recency of previous usage*," which is measured as time (in weeks) since a consumer's previous usage of any decision aid; and "*number of different decision aids used*," which is the number of different decision aids a consumer has used prior to week t. Details of these decision aids and variable computation are described later.

Note that in our model, consumer heterogeneity is accounted for by the individual-specific cut-off points and time-varying variables (D_{it}) in the state transition probability functions. They capture individual differences in their initial purchase behavior as well as behavior evolution, and thus accommodate heterogeneity in parameter values in the store visit and shopping trip spending model in each time period. We apply Bayesian MCMC techniques and estimate the model following the approach by Netzer et al. (2008, pp. 191–192). The prior distributions of parameters in our model are described in Web Appendix A (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0872).

4. Empirical Analyses

4.1. Data Description

Our data are provided by a leading Internet grocery retailer that was among the very first to sell groceries online in the United States. The data set was collected during a 62-week period in 1996–1997 when the retailer first launched its Web business. Given that this retailer was a pioneer of the online grocery business, it is very likely that consumers in our data never had prior exposure to other online grocery stores. This feature makes the data set particularly suited to study the evolution of purchase behavior in a new online shopping environment. The data include click-stream records of detailed online navigation processes as well as households' purchase history records in the store. We chose to include those households that made at least two purchases from the online store during the 62-week period, which yielded 247 households in the store-level estimation data. On average, these households made 20 shopping trips to the online store on an annual basis and spent $123 per trip.

To assess the robustness of results obtained from the store-level model and to examine potential differences in the patterns across product categories, we also applied a similar model to study category-level purchase incidence and quantity decisions. We used purchase frequency and food versus nonfood as the classification scheme to choose categories for the following reasons. Purchase frequency has been shown to be an important category characteristic that affects in-store decision making (e.g., Inman et al. 2009) and promotion elasticity (e.g., Narasimhan et al. 1996). Since the context of this study is online *grocery* stores for which food products play a uniquely important role, and food and nonfood products differ drastically in certain features (such as relevance to nutrition and stockpilability), the impact of decision aid usage experience on purchase behavior may also differ between them. Using median-split for purchase frequency, we chose the following eight categories with two for each subtype: higher purchase frequency (HPF) food categories included butter and spaghetti sauce, HPF nonfood categories included paper towels and toilet paper, lower purchase frequency (LPF) food categories included ground coffee and saltine crackers, and LPF nonfood categories included liquid detergent and soap bars.

4.2. Operationalization of Key Variables

As explained previously, we use store-level aggregated regular price and price cut as the key marketing mix variables for the store visit and shopping trip spending model in our empirical analysis. The online retailer made available to us stock-keeping unit (SKU) level price and promotion data for a market basket consisting of 14 categories spanning across food, beverage, household cleaning, and personal care products. We use data of this market basket to construct store-level price and promotion variables. The specific operationalization of our store-level price and promotion variables is very similar to that used by Zhang and Breugelmans (2012) and they take into account household-specific category

Table 1 Types of Online Decision Aids Examined

Broad category	Decision aid	Definition
For nutritional needs	Sort by nutrition	Sort by nutritional criteria, including calories, sodium, fat, kosher, sugar, carbohydrates, fiber, and cholesterol
For brand preference	Sort by brand name	Sort by brand name
For economic needs	Sort by price	Sort by price information, including unit price and item price
	Sort by promotion	Sort by promotion status
Personalized shopping lists	Shopping list	Retrieve and use a personal shopping list
	Previous order list	Retrieve and use a previous order list

importance.[1] For the category-level models, we computed the weighted average unit regular price and price cut across all SKUs in a category.

Decision aid usage information is extracted from the click-stream data. We identify six interactive decision aids used by the focal retailer, all of which are offered by various present-day online (grocery) retailers. They fall into one of the four broad categories of decision aids described earlier, including one for nutritional needs, one for brand preference, two for economic needs, and two for personalized shopping lists (see Table 1). For each decision aid, we measure a household's usage experience by week t as the cumulative number of usage counts up to the prior week $t-1$. This measure does not include usage information in week t and thus avoids possible reverse causality, that is, purchase behavior may influence the usage of decision aids on the current shopping occasion. Note that a household can use the same decision aid multiple times during a single shopping session and the cumulative experience variables count each and every time a given decision aid is used by a household. The usage experience variables are included as covariates in the transition probability functions part of our proposed hidden Markov model. Since the usage experience with each decision aid increases monotonically with time and thus is highly correlated with each other, a more meaningful measure to include in the model is the relative usage experience of each decision aid, computed as a percentage of a household's total number of usage count of all decision aids up to week $t-1$. We also include the total decision aid usage count, number of different decision aids used, and recency of previous decision aids usage in the transition probability functions to account for their potential effects. Descriptive statistics of the usage experience variables are presented in Table 2. Since we need to exclude at least one of the relative usage

[1] Details are available from the authors upon request.

Table 2 Descriptive Statistics of Decision Aid Usage Experience Variables

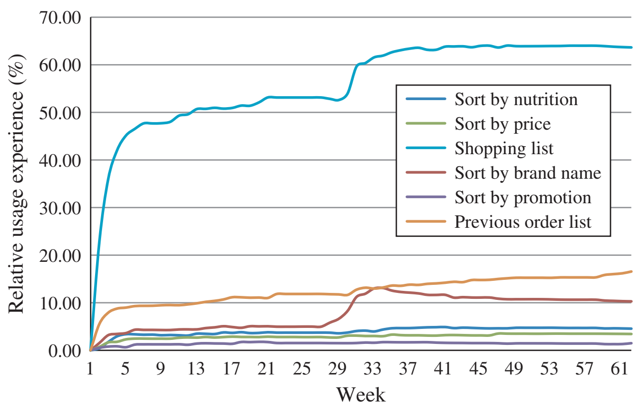
	Count		As a percentage of total decision aid usage (%)	
Variable	Mean	S.D.	Mean	S.D.
Cumulative usage up to week $t-1$:				
—*Sort by nutrition*	1.10	4.32	3.95	9.84
—*Sort by brand name*	2.42	6.49	8.24	16.86
—*Sort by price*	0.78	2.30	2.87	7.98
—*Sort by promotion*	0.26	0.75	1.46	5.76
—*Shopping list*	17.26	30.88	55.92	37.00
—*Previous order list*	2.82	5.86	12.46	21.36
—*Total decision aid usage*	24.65	38.70		
—*No. of different decision aids used*	2.35	1.59		
Cumulative usage by week 62:				
—*Sort by nutrition*	2.00	6.44	4.56	9.18
—*Sort by brand name*	4.23	8.68	10.52	17.98
—*Sort by price*	1.22	3.09	3.19	9.19
—*Sort by promotion*	0.39	0.92	1.53	5.43
—*Shopping list*	31.65	48.00	63.57	31.22
—*Previous order list*	5.49	9.08	16.64	23.23
—*Total decision aid usage*	44.99	58.03		
—*No. of different decision aids used*	3.17	1.40		
Recency of previous usage (weeks)	5.45	8.33		

experience variables from the model to avoid perfect collinearity, we choose to take out sorting by promotion because it had the lowest usage frequency among the six decision aids studied. The correlations among the relative usage experience variables and the other usage pattern variables in the estimate data are very low in general (see Web Appendix B).

4.3. Time-Varying Patterns of Usage Experience with Decision Aids

To inspect how shoppers' usage patterns of the different decision aids may evolve over time, we take the average of each relative usage experience variable in a week across households and plot them over time (see Figure 1). Note that the relative usage experience measures do not necessarily sum up to 100% in all weeks because some households had not made any store visits and/or tried any decision aids in the earlier weeks. We find that the relative usage experiences with shopping lists and previous order lists increased over time and dominated the other decision aids, whereas the relative usage experiences with sorting by brand name, nutritional information, price, and promotion leveled off in the later stage of the observation period. As discussed in §2, the usage of shopping lists and previous order lists is indicative of habitual decision processes, whereas the usage of decision aids for searching specific product attributes suggests on-the-spot

Figure 1 Time-Varying Patterns of Usage Experience with Decision Aids



decision processes. So the above patterns indicate that, on average, consumers gravitated toward habitual decision behavior and made fewer on-the-spot decisions as they became more accustomed to the type of online shopping environment studied here.

4.4. Store-Level Model Estimation Results

We will focus on describing estimation results of the store-level models here, and will provide a discussion of the category-level results in §4.6. Comparisons of the log-marginal densities (LMD), Bayesian information criterion (BIC), and deviance information criterion (DIC) of models with different numbers of hidden states indicate that a three-state store-level model fits the data best.[2] Estimation results of the final model are presented in Table 3.

As shown in Table 3, purchase behaviors differ substantially across the three hidden states. By the construction of the model, the baseline store visit tendencies are in ascending order from hidden state 1 (S1) to hidden state 3 (S3). The estimation results show the same order of baseline tendency across states for the shopping trip spending part, even though these parameters are not constrained to be so. Parameter estimates indicate that S1 represents a low store loyalty and medium price and promotion sensitivity state, S2 is characterized by medium store loyalty and the highest price and promotion sensitivities, and S3 exhibits the highest store loyalty and the lowest price and promotion sensitivities.

The lower panel of Table 3 reports parameter estimates of the transition probability functions. The main findings are the following: (1) Prior usage experiences with decision aids significantly[3] influence consumers' transitions between the different behavioral states. (2) The impact varies by the specific decision aid. More prior usage experience with sorting by nutrition, shopping lists, and previous order lists increases a consumer's probability of transitioning to a higher store loyalty state, whereas more prior usage experience with sorting by price and sorting by brand name has the opposite effect. (3) The total decision aid usage and variety of decision aids used increase a consumer's probability of transitioning to a higher store loyalty state, and the longer since she used any decision aid previously the more likely she will stay in a low store loyalty state. (4) Usage experience of which decision aids exert a significant impact on purchase behavior also depends on the specific behavioral state that a consumer is in. For example, the effect of sorting by brand name on reducing store loyalty is significant only in S1 but not in S2 and S3.

A plausible reason for the negative effect of usage experience with sorting by brand name on store loyalty in S1 is that, as is typical for online *grocery* stores, the focal retailer carried a smaller assortment than the average offline supermarket, and with heightened brand preferences induced by usage experience with sorting by brand, consumers might be more willing to switch stores if their preferred brands were unavailable in the focal store, especially when their loyalty to the store was still low.

4.5. Evolution of Purchase Behavior in the Online Store

Although the states identified by the model do not necessarily follow any time order, the above results imply that consumers' purchase behaviors may evolve over time in a certain direction in a new online store environment, which we examine in this section.

4.5.1. Probabilities of Belonging to the Hidden States. To better understand the evolution patterns of purchase behavior, we compute each household's filtering probability of belonging to state s in each week[4] and then plot the average probability of belonging to each of the states over time across all households (see Figure 2). Figure 2 shows clearly that consumers' purchase behavior in the online store had evolved through distinct states over time. The average probability of belonging to S1 (which has the lowest tendency to purchase from the focal store) decreased substantially, whereas the average probabilities of belonging to S2 and S3 increase over time. On average, S1 was the most likely state till week 33, and S3 (which has the highest purchase tendency) became the dominant behavioral state after week 38.

[2] See Table B2 in Web Appendix B for details.

[3] For the ease of exposition, we use the term "significant" hereafter to refer to the cases where the posterior 95% credible interval does not cover zero.

[4] The computation detail is available from the authors upon request.

Table 3 Store-Level Model Estimation Results

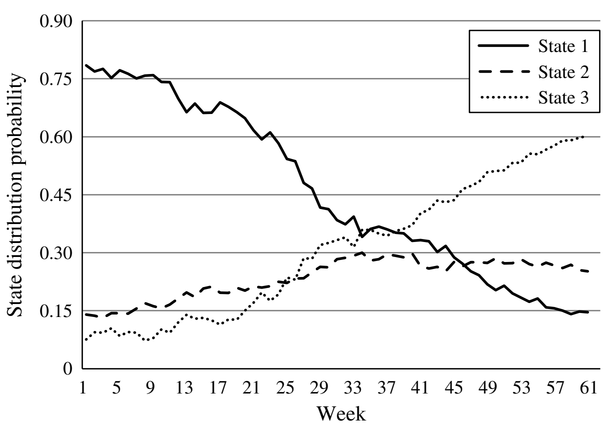
	Hidden state 1 (S1)			Hidden state 2 (S2)			Hidden state 3 (S3)		
Variables in the Tobit model	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Store visit incidence									
Intercept	**−0.673**	−1.055	−0.290	**1.658**	1.096	2.220	**1.974**	1.469	2.480
Regular price	**−0.262**	−0.360	−0.163	**−0.812**	−1.277	−0.347	**−0.132**	−0.194	−0.070
Price cut	**0.283**	0.086	0.481	**0.996**	0.751	1.242	0.124	−0.557	0.805
Shopping trip spending									
Intercept	**−1.451**	−1.853	−1.050	**0.895**	0.144	1.646	**3.624**	2.325	4.924
Regular price	**−0.685**	−1.139	−0.232	**−1.624**	−2.324	−0.925	−0.396	−2.132	1.340
Price cut	0.423	−0.090	0.937	**0.983**	0.056	1.910	0.130	−0.029	0.289

	Hidden state 1 (S1)			Hidden state 2 (S2)			Hidden state 3 (S3)		
Variables in the transition probability functions	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Cut-off point 1	**−1.278**	−2.452	−0.104	−0.420	−0.968	0.128	**−0.424**	−0.465	−0.384
Cut-off point 2	**−0.724**	−1.267	−0.181	**1.751**	1.333	2.169	**0.896**	0.738	1.054
Sort by brand name	**−0.982**	−1.446	−0.518	−0.337	−2.695	2.020	0.042	−0.111	0.194
Sort by price	**−0.694**	−0.952	−0.437	**−1.921**	−3.045	−0.796	−0.390	−0.898	0.119
Sort by nutrition	−0.136	−1.545	1.273	**0.351**	0.125	0.577	**0.764**	0.065	1.462
Shopping list	**0.585**	0.330	0.841	**1.392**	0.666	2.119	**1.283**	0.989	1.577
Previous order list	0.307	−0.425	1.039	**0.357**	0.092	0.622	**1.096**	0.732	1.460
Total decision aid usage	0.941	−0.307	2.189	**0.497**	0.133	0.860	**1.081**	0.417	1.746
No. of different decision aids used	**0.302**	0.221	0.384	0.241	−1.446	1.928	0.095	−0.534	0.724
Recency of previous usage	**−0.614**	−0.896	−0.332	−0.110	−1.154	0.934	−0.210	−0.901	0.480

Note. The bold font indicates that the 95% credible interval does not cover zero.

4.5.2. Evolution of Price and Promotion Sensitivities Over Time. Since the purchase behavior states identified by our model are not in ascending or descending order in terms of price and promotion sensitivities, we first compute posterior price and promotion sensitivity measures for each household in each week and then look at the time-varying patterns of price and promotion sensitivity changes in the store. We find that the average values of price and promotion sensitivities increased first and then decreased over the observed period. In addition, their standard deviations rose continuously, indicating that consumers' price and promotion sensitivities became more divergent over time, with most becoming less price sensitive and less promotion sensitive but some evolving in the opposite direction.

Figure 2 Evolution of Purchase Behavior Over Time



4.5.3. Effects of Decision Aid Usage Experience on Price and Promotion Sensitivities. Since the model estimation results do not directly reveal how usage experience with various decision aids affects price and promotion sensitivities, we conduct follow-up regression analyses to answer this question. In a nutshell, the dependent variables are estimates of the price and promotion parameters from the model, and the explanatory variables are the decision aid usage experience variables in the transition probability functions. We specify a random-effect formulation to allow consumer heterogeneity in the price or promotion sensitivity, and use the simulated maximum likelihood estimation (SMLE) method to take into account estimation uncertainty of the price and promotion parameters.[5]

Results of these regression analyses are presented in Table 4. The main findings are the following: (1) Prior usage experiences with shopping lists, previous order lists, and sorting by nutrition significantly reduce consumers' price and promotion sensitivities. (2) Prior usage experience with sorting by price significantly increases price and promotion sensitivities. None of

[5] More details are available from the authors upon request.

Table 4 Effects of Decision Aid Usage Experience on Store-Level Price and Promotion Sensitivities

	Regular price coefficient		Price cut coefficient	
Explanatory variables	Store visit incidence	Shopping trip spending	Store visit incidence	Shopping trip spending
Intercept	−0.447***	−0.950***	0.435***	0.506***
Log(intercept variance)	−1.238***	−1.535***	−0.993***	−1.168***
Sort by brand name	−0.135	−0.054	0.113	0.073
Sort by price	−0.106**	−0.078*	0.067***	0.045
Sort by nutrition	0.043*	0.034	0.056	−0.082
Shopping list	0.071***	0.053***	−0.094***	−0.080***
Previous order list	0.017***	0.019***	−0.082***	−0.062***
Total decision aid usage	5.13E–05	7.27E–05	−5.77E–05	−6.4E–05
No. of different decision aids used	0.042	0.037	−0.007	−0.010
Recency of previous usage	−6.26E–04	−7.67E–04	4.92E–04	1.01E–04

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01.

the other usage experience variables appear to have significant effects.

4.6. Category-Level Model Estimation Results and Cross-Category Comparisons

The results of category-level models for the eight product categories are consistent with and further validate the store-level findings (see Web Appendix C for detailed estimation results).[6] Briefly speaking, BIC, DIC, and LMD statistics indicate that a three-state model fits the data best for all categories. These states differ in their baseline category purchase tendency and price and promotion sensitivities in the same fashion as revealed by the store-level model. Consumers evolved from lower purchase tendency states to higher purchase tendency states over time, and their average price and promotion sensitivities first increased then decreased. In general, prior usage experiences with shopping lists and previous order lists and the total decision aid usage increase consumers' tendency to purchase from the focal store, and their impact tends to be stronger in the higher purchase tendency states. In contrast, when consumers are in lower-purchase-tendency states, the variety and recency of decision aid usage increase their probability of transitioning to a higher purchase tendency state, whereas usage experiences with sorting by brand name and by price reduce their purchase tendency. Moreover, usage experiences with shopping lists and previous order lists have the most prominent effects of reducing price and promotion sensitivities, whereas usage experiences with sorting by brand name and sorting by price show the opposite effects.

The categories also exhibit some interesting differences in terms of the extent of impact of usage experience with different decision aids on purchase behavior evolution. Table 5 presents the number of significant effects in the state transition probability functions and in the SMLE regression models for price and promotion sensitivities, by decision aid and types of product categories. The main findings are the following: (1) The effect of sorting by price on increasing promotion sensitivity is stronger for HPF categories than for LPF categories. This can be explained by the fact that consumers are more sensitive to price changes in HPF categories (e.g., Narasimhan et al. 1996) and thus more likely to use sorting by price when purchasing these categories. (2) The effects of sorting by nutrition on increasing purchase tendency and reducing promotion sensitivity are stronger for HPF food categories than for LPF food categories. This makes sense because consumers tend to place higher importance on HPF categories and thus more likely to search nutritional information of these products. (3) The effects of shopping lists and previous order lists on increasing purchase tendency and reducing promotion sensitivity are stronger for HPF categories than for LPF categories. Prior research shows that HPF categories are more likely to be included in shopping lists (Block and Morwitz 1999) and bought as planned purchases (Inman et al. 2009, Kollat and Willett 1967). They are also more likely to appear in previous order lists. In addition, their promotion elasticities are higher (Narasimhan et al. 1996) and thus there is more room to be reduced by external factors. (4) The effect of sorting by brand name on reducing purchase tendency is stronger for nonfood categories than for food categories. This is likely due to the fact that online *grocery* retailers usually carry a small assortment of nonfood categories with limited brands, and thus consumers are more likely to miss their preferred brands in nonfood categories and switch stores as a result. (5) The effect of shopping lists on reducing promotion sensitivity is stronger for nonfood categories than for food categories. A plausible reason is that promotion elasticity is shown to increase with the ability to stockpile (Narasimhan et al. 1996), and nonfood products have higher stockpilability than food products (which are perishable) and thus higher promotion sensitivities, leaving more room to be reduced by external factors. (6) Sorting by nutrition exerts significant effects only in food categories to which the nutritional attributes are relevant.[7] This attests to our model's ability to

[6] We have computed and tested category-specific usage experience variables for the category-level models, and found that the store-level measures have better explanatory power. Therefore, store-level usage experience variables are used in the final models.

[7] We did not find any significant effects of usage experience with sorting by nutrition in the coffee category, which is not surprising because none of the sortable nutritional attributes available at the time was relevant to coffee.

Table 5 **Number of Significant Effects of Decision Aid Usage Variables Across Product Categories**

	Sort by brand name	Sort by price	Sort by nutrition	Shopping list	Previous order list	Total decision aid usage	Variety of decision aid usage	Recency
On purchase tendency								
Food	4	5	4	10	8	3	3	1
Nonfood	8	7	0	9	8	10	3	5
Higher purchase frequency	6	6	3	11	8	7	5	4
Lower purchase frequency	6	6	1	8	8	6	1	2
On price sensitivity								
Food	1	2.5	3	6	3	0.5	0	0
Nonfood	4	3.5	0	8	6.5	3	0	0
Higher purchase frequency	1.5	3.5	2	6	3.5	2	0	0
Lower purchase frequency	3.5	2.5	1	8	6	1.5	0	0
On promotion sensitivity								
Food	0	1	2	5	4.5	0	0	0
Nonfood	2	1.5	0	7	4.5	0	0	0
Higher purchase frequency	2	2.5	2	8	7	0	0	0
Lower purchase frequency	0	0	0	4	2	0	0	0

Note. Effects that are significant at $\alpha = 10\%$ level are each counted as 0.5.

detect effects when they are expected and not to yield false positives when they are not expected. In general, the impact of usage experience with decision aids on purchase behavior evolution appears to be stronger for higher-purchase-frequency categories and nonfood categories.

5. Key Findings and Managerial Insights

The key findings of this study and their managerial implications are summarized in Table 6. We elaborate on several of them here.

(1) Consumers evolved through distinct behavioral states in a new online shopping environment, and the evolution was attributable to their prior usage experience with various interactive decision aids available in the store. This implies that online retailers can infer the behavioral state each customer is in at any given time point by tracking his or her decision aid usage patterns and utilizing estimation results of our proposed model. Such insight can help them design a variety of customized promotion programs.

(2) The impact of prior usage experience on purchase behavior evolution varies by the specific decision aid. Our results identify three decision aids that can help online (grocery) retailers enhance store loyalty and mitigate the pressure of price and promotion competitions: shopping lists, previous order lists, and sorting by nutrition, with the first two having the most prominent beneficial impact. The results also point to potential undesirable consequences of arguably the two most popular decision aids: sorting by price and sorting by brand. Both may reduce store loyalty, and the former could also increase consumers' price and promotion sensitivities. These findings can benefit many present-day online (grocery) retailers as most of them have not implemented all of the beneficial decision aids we have identified in this study. In addition, our proposed model can be applied to study the impact of other decision aids, for example, sorting by customer ratings and sorting by best sellers that have been implemented by many retailers in recent years.

Prior research has found systematic differences in consumers' purchase behavior in online and offline stores. Besides intrinsic differences between online and offline consumers because of self-selection, it has been postulated that unique features in the online shopping environment may contribute to the observed behavioral differences (e.g., Alba et al. 1997, Degeratu et al. 2000, Zhang and Wedel 2009). Our study provides empirical support to this conjecture and pinpoints the specific causes for certain behavioral differences reported previously. For example, Zhang and Wedel (2009) find that online consumers are less promotion sensitive and more state dependent than their offline counterparts. Our analyses show that online consumers' usage experiences with shopping lists and previous order lists have contributed to this pattern.

(3) Consumers evolved through behavioral states that vary in price and promotion sensitivities. The average price and promotion sensitivities first increased and then decreased, but the level of heterogeneity rose continuously over time. This implies that online stores provide a conducive environment for customized promotions, as prior research finds that a higher degree of heterogeneity in promotion sensitivity leads to greater payoffs of more granular price promotion customizations (Zhang and Wedel 2009). Online retailers can utilize the methodology and findings of this research to design customized price promotions for individual categories. For example, a simple strategy is to target price discounts to consumers when and only when they are in a promotion-sensitive state (S1 or S2). Our

Table 6 Summary of Key Findings and Their Managerial Implications

Findings	Managerial implications
General results based on store- and category-level models	
Consumers evolved through distinct behavior states over time, and the evolution was attributable to their prior usage experience with various decision aids.	Online retailers can infer the behavioral state each customer is in at any given time point by tracking his or her decision aid usage data and utilizing estimation results of the proposed model.
The impact of prior usage experience on purchase behavior evolution varies by the specific decision aid.	Identified beneficial vs. potentially undesirable decision aids: Online (grocery) retailers should provide and encourage usage of "shopping lists," "previous order lists," and "sorting by nutrition," and be cautious about "sorting by brand" and "sorting by price," which can yield undesirable consequences (e.g., reducing store loyalty).
The impact of prior usage experience of decision aids on purchase behavior evolution varies by the behavioral state a consumer is in.	Online retailers should modify their promotions and communication messages based on the behavioral state a consumer is in and what the most effective decision aids are for that state (which are revealed by our model).
The average price and promotion sensitivities first increased and then decreased, whereas their standard deviations rose continuously.	• Online retailers can customize promotions by offering them when and only when a consumer is identified to be in a promotion-sensitive state (S1 or S2). • Online stores provide a conducive environment for promotion customizations because of the increasing consumer heterogeneity in promotion responsiveness.
Cross-category differences in the impact of prior usage experience with decision aids on purchase behavior evolution	
Sort by price. Effect of increasing promotion sensitivity is stronger for HPF categories.	Online retailers should be mindful of the impact of sorting by price, and should focus on HPF categories when increasing promotions in response.
Sort by nutrition. Effects of increasing purchase tendency and reducing promotion sensitivity are stronger for HPF food categories.	Online grocery retailers should encourage the usage of decision aids for nutritional needs especially for HPF food products.
Shopping lists and previous order lists. Effects of increasing purchase tendency and reducing promotion sensitivity are stronger for HPF categories.	Providing and encouraging the usage of shopping lists and previous order lists can help online retailers achieve higher sales gains from HPF categories than from LPF categories.
Sort by brand name. Effect of reducing purchase tendency is stronger for nonfood categories.	Online grocery retailers need to watch out for the negative impact of decision aids for brand preference on their store loyalty, especially in their nonfood categories.
Shopping lists. Effect of reducing promotion sensitivity is stronger for nonfood categories.	Online grocery retailers that offer shopping lists could focus on nonfood categories when reducing promotion activities.
Based on descriptive analyses	
Consumers gravitated toward habitual decision processes and made fewer on-the-spot decisions in the online store.	• Consumers tend to use different decision heuristics in online vs. offline stores. • Online retailers can use certain decision aids (e.g., shopping lists, previous order lists) to foster planned purchases.

simulation analyses indicate that this strategy could lead to a 4.6% increase in category sales while reducing promotion spending by 38.4% on average,[8] and the sales gains are stronger for HPF categories (7.1% on average).

(4) There are cross-category differences in the extent of impact of usage experience with decision aids on purchase behavior evolution. In general, the impact appears to be stronger for higher-purchase-frequency and nonfood categories. For example, the effects of shopping lists and previous order lists on increasing purchase tendency are stronger for HPF categories. Online retailers can track each consumer's decision aid usage patterns and offer targeted incentives for using shopping lists and previous order lists to those consumers who had not used them. This strategy would lead to greater sales gains in HPF categories, as is confirmed by our simulation analyses. (Table 6 provides more managerial implications of the cross-category differences.)

(5) As consumers learned and adapted to the online store, they tended to engage in habitual decision processes and to gravitate toward decision aids that enabled them to complete purchase tasks with minimal cognitive efforts, as opposed to those that allowed them to search for product attribute information more efficiently and effectively. This is an intriguing contrast with previous findings on decision making in brick-and-mortar stores where most purchases were found to involve in-store decision making. It suggests that, although consumers tend to minimize their cognitive efforts for grocery shopping (Hoyer 1984), the decision heuristics that they employ to minimize cognitive efforts are different in online and offline stores. Prior research (e.g., Inman et al. 2009, Park et al. 1989) shows that the many sensory stimuli available in physical stores can trigger unrecognized or forgotten needs, thus consumers tend to rely on in-store cues (such

[8] Details of all simulation analyses referenced here are available from the authors upon request.

as special displays and shelf layouts) to assist their purchase decisions. In contrast, there are few sensory stimuli in online stores, which may explain why most consumers tend to rely on preconstructed shopping lists or previous order lists to assist their purchase decisions.

An important direction for future research is to formally test alternative theories about the underlying decision processes and decision heuristics in the Internet shopping environment. In addition, it would be interesting to investigate whether there are carry-over effects of usage experience across product categories. Given the proliferation of multichannel retailing, another worthy direction is to study the impact of usage experience with online decision aids on offline purchase behavior. All of these topics offer exciting venues for gaining a deeper understanding of purchase behavior evolution in the ever-evolving retail landscape.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0872.

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