ABSTRACT

Title of Document:	**DYNAMIC CONSUMER DECISION MAKING PROCESS IN E-COMMERCE**
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This dissertation studies the dynamic decision making process in E-commerce. In the first essay, we use eye tracking to investigate how consumers make information acquisition decisions on attribute-by-product matrices in online choice environment such as comparison websites. Hierarchical Hidden Markov Model is used to describe this process. The model consists of three connected hierarchical layers: a lower layer that describes the eye movements, a middle layer that identifies product- and attribute-based information acquisition modes, and an upper layer that flexibly captures switching between these modes over time. Findings of a controlled experiment show that low-level properties of the eye and the visual brain play an important role in dynamic information acquisition. Consumer switch frequently between two acquisition modes, and higher switching frequency increases decision time and reduces easiness of decision making.

These results have implications for web design and online retailing, and may open new directions for research and theories of online choice.

The second essay investigates how usage experience with different types of decision aids contributes to the evolution of online shopping behavior over time. In the context of online grocery stores, we categorize four types of decision aids that are commonly available, namely, those 1) for nutritional needs, 2) for brand preference, 3) for economic needs, and 4) personalized shopping lists. We construct a Non-homogeneous Hidden Markov Model of category purchase incidence and purchase quantity, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids. The dataset was collected during the period when the retailer first launched its web business, which makes it particularly suited to study the evolution of online purchase behavior. We estimate the model for the spaghetti sauce and liquid detergent categories. Results indicate that four types of decisions influence evolution of purchase behavior differently. Findings from this study enrich the understanding of how purchase behavior may evolve over time in online stores, and provide valuable insights for online retailers to improvement the design of their store environments.

DYNAMIC CONSUMER DECISION MAKING PROCESS IN E-COMMERCE

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2011

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Acknowledgements

I am heartily thankful to my advisor, Dr. Michel Wedel, whose encouragement, caring, guidance and support enabled me to explore the exciting new subject and complete this dissertation. The joy and enthusiasm he has for research is contagious and motivational for me, even during tough times in the Ph.D. pursuit. I would like to thank Dr. Jie Zhang, who sets an example of a great researcher for her rigor and passion on research. She has assisted, advised, and supported my research and writing efforts over the last five years. I am also grateful for Dr. Michael Trusov, who has generously given his time and expertise to better my work, and helped me to gain a different perspective to the research problem. Special thanks goes to Dr. P.K. Kannan and Dr. Ginger Zhe Jin, who graciously agreed to serve on my defense committee. I am also in debt to Dr. Rik Pieters, whose remarkable insights and valuable suggestions have contributed greatly to the completion of this dissertation. My deepest gratitude goes to my parents for their unconditional love and support throughout my life; this dissertation is simply impossible without them.

Table of Contents

List of Tables

List of Figures

Chapter I: General Introduction

This dissertation is composed of two essays in the discipline of dynamic consumer decision making in E-commerce. The global E-commerce has experienced robust growth in recent years, and its revenue is predicted to reach 680 billion dollars by the end of 2011, a 18.9% increase from 2010[1]. Online shopping websites have become popular channels in which consumers acquire product information and make purchase decisions. Shopping behavior in online stores has been shown to be systematically different from that in offline stores (e.g., Danaher, Wilson, and Davis 2003, Degeratu, Rangaswamy, and Wu 2000, Zhang and Wedel 2009), and such observed behavioral discrepancy can be partially attributed to the differences in shopping environments (Zhang and Wedel 2009). The availability and display of product-attribute information, and the design of interactive decision aids, may all affect consumers' information search and evaluation processes, purchase decision making, and the evolution of shopping behavior in online stores. In this dissertation, we intend to empirically investigate the impact of the online shopping environment on consumers' purchase decision processes, and how consumers adapt to this increasingly prominent channel. Essay one focuses on the dynamic information acquisition decisions on comparison shopping websites, and essay two studies the evolution of purchase decisions in online grocery stores. In both situations, consumers' behavior at one stage may influence their behavior at a later stage. We empirically examine how consumers dynamically adjust their decision strategies based on the newly acquired information or experience, in the web-based choice environment. Findings from this dissertation will enrich the understanding of the dynamic decision making in the information-rich online shopping

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1 E-Commerce Report from JP Morgan senior analyst Imran Kahn, http://techcrunch.com/2011/01/03/j-p-morgan-global-e-commerce-revenue-to-grow-by-19-percent-in-2011-to-680b/

environment, and provide valuable insights for online retailers to improve the design of their store environments.

Dynamic decision making is a field with long tradition in marketing. Constructive decision making theory proposes that during the decision process, consumers incorporate new information, develop new standard and construct the decision contingent on task environment (Bettman and Park1980; Bettman, Luce and Payne 1998). Therefore, decision strategies over time are interrelated and the decision process is dynamic. Various models have been developed to study this phenomenon. Time series models, such as autoregressive (AR) and moving average (MA) models, are used to reveal the over-time impact of marketing variables and make forecast of purchase behavior (e.g., Dekimpe and Hanssens 2000). The Vector Autoregression (VAR) model is suitable for studying dynamic interactions (e.g., Dekimpe and Hanssens 1995). State dependence models are developed to accommodate dynamics in purchase behavior by including three types of variables: lagged choices such as brand loyalties; lagged marketing variables such as decaying effects of advertising; and serially correlated error terms in the random utility function that account for reasons unknown to the researchers (e.g., Erdem 1996; Guadagni and Little 1983; Heckman 1981, Seetharaman, Ainslie, and Chintagunta 1999). All these models have made important contributions in studying dynamics of marketing phenomena.

Thanks to recent development in technology, dynamics in the decision making process has been approached from a new angle: the use of path data (Hui, Bradlow, and Fader 2009a; 2009b). Path data is defined as the "consumers' movement in a spatial configuration", and records "consumers' interaction with his environment to achieve his goal" (Hui et al. 2009b). Grocery shopping paths, eye tracking data, online navigation data, etc., all belong to this category. The beauty of path data lies in its ability to capture the information search and

evaluation processes during decision making, which enables researchers to exploit micro-level dynamics, and thus offers exciting new research opportunities for this topic.

Researchers have acknowledged the importance of path data in deepening the understanding of decision processes: Underhill (2004) makes recommendation on shopping environment design based on the analysis of consumers' shopping paths; Hui et al. (2009a) develop an integrated individual level probability model where consumers' entire shopping path is used to predict store visit and purchase probabilities. Eye-movement paths are another type of path data that gaining ground in study decision dynamics, especially in the advertising research (Pieters and Warlop 1999; Rayner 1998; Rosbergen, Pieters, and Wedel 1997). Researchers use eye trackers to analyze consumers' eye fixation paths on advertisements and optimize the design of them (Pieters and Wedel 2004; Pieters, Wedel and Zhang 2007). Online navigation data offers great detail on navigation behavior during decision making. It records activities that reflect consumers' preference, provides insights in how consumers search and evaluate information before purchase, and therefore enables researchers to better interpret and predict online shopping behavior. Bucklin and Sismeiro (2003) use previous websites visit depth and breadth (numbers of websites visited) to explain web page browsing strategies. Montgomery and his colleagues (2004) use sequence of the page viewed to predict the subsequent online navigation path. In this dissertation, we focus on two types of path data, namely, eye movement paths (essay 1), and online navigation paths (essay 2), and explore how the information extracted from the path data help to explain dynamic information acquisition decisions and the evolution of purchase decisions.

Following up on calls for a flexible evolutionary structure to represent decision dynamics (Erdem 1996; Hauser and Wisniewski 1982; Heilman , Bowman, and Wright 2000), we provide

two approaches for modeling dynamic decision making processes, both fall under the hidden Markov model framework. Hidden Markov Model (HMM) is a popular probabilistic model for sequence data analysis. The fundamental premise of HMM is that there several hidden states governing the observed behavior, and the transitions among these hidden states follow a Markov process. The probabilistic model effectively extracts diagnostic information from sequence data, and automatically assigns the observed behavior into latent states, taking uncertainty into account. The HMM and its extensions are able to flexibly capture the dependence and dynamics in the decision making process, and has been widely used in a variety of disciplines (e.g., Rabiner and Juang 1986; Baldi, Hunkapiller, and Chauvin 1994; Kupiec 1992), including marketing (Brangule-Vlagsma, Pieters, and Wedel 2002; Du and Kamakura 2006; Montgomery, et al. 2004; Netzer, Lattin and Srinivasan 2008; Liechty, Pieters and Wedel 2003; Van derLans, Pieters and Wedel 2008).

Eye movements are fast, adaptive, and partially automatic. The information acquisition strategies that direct the eyes in searching for information, however, are latent cognitive states. In addition, the link between eye movement and the unobservable information acquisition strategies is probabilistic rather than deterministic (Lohse and Johnson 1996; Wedel and Pieters 2000). Therefore, in essay one, we propose a new Hierarchical Hidden Markov Model (HHMM) for the analysis of dense eye-movement data. The proposed model extends the standard HMM by adding another layer of latent states. It is a special case of Hierarchical Hidden Markov Model (HHMM; Fine, Singer, and Tishby 1998; Heller, The, and Görür 2009), which has been used in the recognition of human activity (e.g., Kawanaka, Okatani, And Deguchi, 2006), information extraction, (e.g., Skounakis, Craven, and and Ray 2003), and lexical graphic analysis (e.g., Zhang, Yu, Xiong, and Liu, 2003). Three layers in HHMM impose a flexible structure on the

4

information acquisition processes: a lower layer that describes the eye movements, a middle layer that identifies product-based and attribute-based information acquisition modes, and an upper layer that captures switching between these modes over time. The model and eye movement data enable us to diagnose the influence of both conscious strategies and low-level properties of the eye and the visual brain on dynamic information processes. The paper empirically investigates the extent of usage and switching of different information acquisition strategies, how much and what information is processed in these strategies, and the causes and consequences of strategy switching.

In essay two, we modify the standard HMM by allowing hidden state transition probabilities to change across time through time-varying covariates, and propose Non-homogeneous Hidden Markov Model (NHMM) to study how the usage of different decision aids drives the purchase behavior evolution in online grocery store. Scholars have applied NHMM in Meteorology and Climatology (Hughes 1993, Hughes and Guttorp 1994a; 1994b); Robertson, Kirshner, and Smyth 2004; Robertson, Ines, and Hansen 2007), and recently, the model is used in studying customer relationship dynamics (Netzer et al. 2008). NHMM is able to identify purchase behavior patterns, which has been a long-standing research interest in the marketing literature. It is especially suitable for studying drivers behind the behavior evolvement. The results reveal how consumers switch among behavior states that differ in purchase propensity and responsiveness to marketing variables, more importantly, how the usage experience with decision aids for economic needs, non-economic needs, brand preference and personalized shopping list affects transitions among latent behavior states differently.

The organization of this dissertation is as follows: Chapters 2 and 3 discuss the two essays in depth, respectively; Chapter 5 briefly summarizes each essay, points out the contributions of this dissertation, and concludes with possible future research avenues.

Chapter II: Information Acquisition during Online Choice:

A Model-Based Exploration

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2.1. Introduction

Retailers and manufacturers are undergoing competitive pressure to assist consumers in the large number of choices of products and services that they make online. During the often short time that it takes to make such a decision, consumers acquire information on the alternatives presented to them and the way in which they do this affects their decision. This is recognized by retailers and manufacturers who try to optimize online information displays, in particular comparison sites that have become popular tools for consumers (for example, Bizrate.com, Dell.com, and Nextag.com each has over 10 million monthly visitors[2]).

In the academic literature, process tracing methods have been proven important in helping to understand how consumers process information (Bettman and Jacoby 1976; Bettman and Kakkar 1977; Johnson, Schulte-Mecklenbeck, and Willemsen 2008; Lohse and Johnson 1996; Payne 1976; Payne, Bettman, and Johnson 1993; Senter and Wedell 1999). Research has revealed two key information acquisition strategies: attribute-based and product-based (Ball 1997; Bettman, Luce, and Payne 1998; Payne et al. 1993). During attribute-based acquisition, information is acquired on a single attribute across multiple products, before going to the next attribute. During product-based acquisition, information is acquired on a single product across multiple attributes, before going to the next product. Findings on these two strategies, however, have been obtained with research methods such as information display boards or Mouselab, in which information becomes available sequentially as consumers manually inspect cells in attribute-by-product displays. The required motor responses necessarily slow down the decision process, and render it more controlled and deliberate (Bettman et al. 1998). As a consequence,

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[2] "15 Most Popular Comparison Shopping Websites|March 2011", from http://www.ebizmba.com/articles/shopping-websites.

8

these prior studies could discover mostly high-level and slower cognitive processes that consumers engage in during decision making.

Comparison sites provide all information on the choice alternatives simultaneously. Then, decisions can be made much faster and information acquisition is more likely under influence of both conscious information acquisition strategies and low-level properties of the eye and the visual brain. Lynch and Srull (1982) call for a methodology that is capable of diagnosing both "overt and covert", and "voluntary and involuntary" aspects of decision processes. Russo (1978), Russo and Leclerc (1994) and Lohse and Johnson (1996) have argued that in such situations eye tracking methodology would be ideally suited to provide insights into how consumers acquire information.

Affordable eye tracking systems are now widely available. Prior eye tracking studies have often displayed products in a holistic, for instance pictorial, fashion (Lohse and Johnson 1996; Pieters and Warlop 1999; Russo and Rosen 1975; Russo and Leclerc 1994), rather than in the form of attribute-by product displays. These latter displays reflect online decision contexts, and increase the potential insights that can be obtained from eye tracking studies. But they also increase the challenge of providing meaningful descriptions of the massive amounts of data that the eye tracking studies produce.

To illustrate this, Figure 2.1 shows the eye movements of a single participant while making a choice, in our study to be described later (participant 36). The decision took only 76 seconds, but involved 140 eye fixations and saccades (excluding re-fixations). Eye fixations are brief moments that the eye is still and information is extracted (about 2 to 4 times per second). Saccades are rapid jumps of the eye between fixations to redirect the line of sight to a new location. During saccades no information acquisition takes place. In the figure, attribute-based

9

and product-based information acquisition strategies are not clearly discernable: the eyes switched 101 times between making horizontal and vertical movements. Switching seems extensive and the question is whether this is due to unpredictability in how people move their eyes, or whether it is a fundamental property of the underlying information acquisition process.

[INSERT FIGURE 2.1 ABOUT HERE]

The present study uses such eye tracking data to investigate information acquisition on attribute-by-product matrices as encountered in online choice environments. We intend to provide a description of how people acquire information in these contexts, investigating the influence of low-level processes, and the extent of usage of and switching between attribute- and product-based information acquisitions. To deal with challenges posed by the amount of data, we develop and test a new hierarchical Hidden Markov model of information acquisition.

2.1.1 Modeling Information Acquisition Processes

Valid inferences about information acquisition strategies should recognize that they are fundamentally unobservable. Eye movements reflect them probabilistically rather than deterministically (Lohse and Johnson 1996; Wedel and Pieters 2000). The information acquisition strategies that we are interested in are latent cognitive states that direct the eyes in searching for information. They can only be inferred from the observed eye movement paths. Whereas describing the patterns of *observed* eye fixations and saccades (as we did in the earlier example may) already be insightful, inferring and describing the latent cognitive states is preferable (Johnson et al. 2008). To be able to identify when during a decision participants acquire information by-attribute and when by-product, we develop a model that builds on and extends previous applications of Hidden Markov Models (HMM) to eye movement data (Liechty, Pieters, and Wedel 2003; Van der Lans, Pieters and Wedel 2008).

We extend previous two-layer HMMs by developing a new model that describes information-acquisition strategies through three hierarchical layers (see Figure 2.2): (1) the lower layer describes the observed eye movements, (2) the middle layer describes unobserved (attribute- and product-based) information acquisition strategies, and (3) the upper layer describes how consumers switch between them. The model captures this moment-to-moment switching pattern through a number of upper layer states that are a-priori unknown. This allows the transition probabilities between information acquisition strategies to vary over time, and overcomes the time-homogeneity of two-level HMMs. The model enables us to identify from moment-to-moment what the probabilities are that participants process information by-product or by-attribute.This makes it possible to investigate post-hoc how often participants switch between attribute-based and product-based information acquisition, and what specific information they process while doing so. Studying information acquisition processes in this manner is not only of theoretical interest, but also provides insights into the usability of comparison websites.

[INSERT FIGURE 2.2 ABOUT HERE]

We first provide the theoretical foundation and formulation of our model. Then we describe the eye movement experiment of decision-making on comparison websites. In the experiment, we manipulate the information presentation format and provide participants a comparison website in either a product-row or a product-column format. These are the two main presentation formats used for comparison sites (e.g., the popular comparison site Bizrate.com uses a product-row format by default, and Dell.com uses a product-column format). It has been previously shown that these formats may facilitate specific information acquisition strategies (Bettman and Kakkar 1977). We then present the results of the model estimation, which reveal the prevalence of low-level processes, and the extent of switching between the two information

11

acquisition strategies. We conduct an extensive post-hoc analysis to investigate why participants switch and how much and what information they process in these states. Finally, we discuss contributions and future research directions.

2.2 Information Acquisition through Eye movements

Prior studies have described high-level cognitive processing during decision-making (Bettman et al. 1998). Yet, when decisions are fast and more automatic, low-level properties of the eye and the visual brain may influence the information acquisition process more. Here, we focus on three aspect of information acquisition: tendencies of horizontal eye movements, of local eye movements, and of switching between information acquisition strategies. Insight into these factors will lead to a better understanding of decision-making in information-rich online choice environments.

2.2.1 Horizontal Eye Movement Patterns

Orderly sequences of eye movements reflect that individuals use systematic information acquisition strategies. In various visual tasks a horizontal, left-right dominance in consumers' eye movements has been observed, such as when reading (Rayner 1998) or searching store shelves (van der Lans et al. 2008). The dominance of horizontal eye movements may be due to the horizontal layout of many visual displays (Tatler and Vincent 2008). If the information presented is largely textual (as is typical for comparison websites), this should facilitate such reading-like patterns even more. But left-to-right eye-movement tendencies also appear to be independent of the layout or features of the display and are caused by the more rapid decline in the resolution of the retina in the vertical than in the horizontal direction (Gilchrist & Harvey 2006). Information acquisition is thus facilitated when the display is organized consistent with this left-

to-right direction (Spalek and Hammad 2005). Therefore, we expect to find a predominant

tendency for left-to-right visual information acquisition, independent of display format.

2.2.2 Local Eye Movement Patterns

The amount of visual detail that can be acquired is highest in the small area around the

exact eye fixation point and rapidly declines towards the visual periphery (Rayner 1998).

Because much of what is present in the periphery is not clearly visible, people need to make eye

saccades when searching for information. It is as if a small attentional "spotlight" moves across

the display, with information being acquired mostly locally within the focus of the spotlight

(Treisman and Gelade 1980). Using a HMM, Liechty et al. (2003) found that information

acquisition from print advertisements indeed took place in a pattern of bursts of multiple

fixations with short saccades on small areas, occasionally separated by one or a few long

saccades to distant areas. A similar pattern is likely to emerge during decision-making on

product-by-attribute displays, where information is mostly textual. Thus, we expect eye

movements – whether attribute-based or product-based – to be mostly confined to contiguous

cells on the information display.

2.2.3 Switching between Information Acquisition Strategies

Figure 2.3 presents a hypothetical product-attribute matrix. In attribute-based acquisition

information is gathered on a certain attribute across products, before processing the next

attribute. Solid arrow A expresses this. In product-based acquisition, information is gathered on

attributes of a particular product before evaluating the next product, as dashed arrow B shows.

The two acquisition strategies are comprised of elementary steps (Ball 1997). We propose that

these are reflected in the eye movements.

13

We thus distinguish three elementary eye movements (saccades) between cells of the comparison matrix. A type-1 saccade is an elementary step in attribute-based information strategy: the eye jumps between two products for the same attribute (dotted arrow 1 in Figure 2.3). A type-2 saccade is an elementary step in product-based information strategy: the eye jumps between two attributes for the same product (dotted arrow 2 in Figure 2.3). A type-3 saccade may have several functions: the eye jumps from a particular attribute for one product to a different attribute for another product. This may reflect a transition between type-1 and 2 eye movements, an exploratory eye movement (Liechty et al. 2003), or may be a corrective eye movement (Rayner 1998). An attribute-based information acquisition strategy thus consists of a sequence of mostly (type-1) attribute-based steps; a product-based information acquisition strategy is characterized by a sequence of mostly (type 2) product-based steps. Precisely how many elementary steps or eye movements would constitute such a strategy is not known.

Consumers switch between information acquisition strategies due to a variety of factors, including task demands (Ball 1997; Pieters and Warlop 1999; Swait and Adamowicz 2001), experienced accuracy-effort tradeoffs (Bettman et al. 1998) and, importantly, the information acquired up to that point (Bettman and Park 1980; Russo and Rosen 1975). Correspondingly, they will switch eye movement directions. Although switching between strategies enables adaptive decision making, it is also effortful (Gopher, Armony, and Greenshpan 2000; de Jong 2000; Rogers and Monsell 1995) and may reduce the perceived ease of the decision process. To our knowledge, the extent of strategy switching in natural tasks such as online choice, and its causes and consequences, have not yet been quantified.

[INSERT FIGURE 2.3 ABOUT HERE]

14

2.3. Model Formulation

2.3.1 Motivation

Our model to identify attribute- and product-based information acquisition is a

Hierarchical Hidden Markov Model (HHMM; Fine, Singer, and Tishby 1998). This model

generalizes Hidden Markov Models (HMM; Rabiner, and Juang 1986), which have been used in

marketing (Du and Kamakura 2006; Montgomery, Srinivasan, and Liechty 2004; Netzer, Lattin,

and Srinivasan 2008), and eye tracking research (Van derLans et al. 2008; Liechty et al. 2003;

Salvucci and Anderson 1998). The link between the observed eye movements and unobservable

information acquisition strategies is probabilistic. For instance, a jump from one attribute to

another in a longer sequence of attribute-based steps has a lower probability to reflect product-

based acquisition, than a similar jump that occurs in a longer sequence of product-based steps.

Therefore, our model needs to capture longer sequences of eye movements. It does this through

three hierarchically related Markov processes, generalizing two-layer HMMs that are constrained

by stationary transition probabilities (Figure 2.2). The lower layer captures (low level) eye

movements; the middle layer of the model captures the attribute-based and product-based

acquisition strategies that drive the eye movements, and the upper layer of the model captures

switching between the two types of acquisition. We intend to use the model as a flexible tool to

describe eye movement patterns and to identify the acquisition strategies that participants use

from moment-to-moment during decision making. We describe and explain those acquisition

strategies in detail, post-hoc.

2.3.2 Specification

We let $i = 1,\ldots, I$ denote participants and $t = 1,\ldots, T$ fixations. We let $y_{i,t} = (a_{i,t}, p_{i,t})$

denote the particular cell in that display defined by attribute (a) and product (p), at eye-fixation t

15

for participant i. In addition, $y_{i,t-1} = (a_{i,t-1}, p_{i,t-1})$ denotes the cell at the previous eye-fixation t-1.

Figure 2.2 presents the hierarchical relationship among the three layers of the model: the lower layer describes eye movements y, the middle layer captures information acquisition states $S^1 = 1, ..., N$, and the upper layer states $S^2 = 1, ..., M$ describe switching between these acquisition states. Correspondingly, the model is represented by three sets of transition probabilities: the lower layer transition probabilities $P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1})$, the intermediate layer transition probabilities $\Pi_{S^2}(S^1_{i,t} \mid S^1_{i,t-1})$, and the upper layer transition probabilities $\Omega(S^2_{i,t} \mid S^2_{i,t-1})$. These are described next.

We formulate the middle layer hidden states $S^1 = 1$ and $S^1 = 2$ such that they represent, respectively, attribute-based and product-based acquisition strategies (Figure 2.2). We assume $P(y_{i,t} \mid y_{i,t-1}) = P(a_{i,t} \mid a_{i,t-1}) \cdot P(p_{i,t} \mid p_{i,t-1})$, given the unobserved state, with $P(y_{i,t} \mid y_{i,t-1})$ the saccade probability from cell $y_{i,t-1}$ to cell $y_{i,t}$, $P(a_{i,t} \mid a_{i,t-1})$ the saccade probability from attribute $a_{i,t-1}$ to attribute $a_{i,t}$, and $P(p_{i,t} \mid p_{i,t-1})$ the saccade probability from product $p_{i,t-1}$ to product $p_{i,t}$. Each of the two middle layer states (attribute-based acquisition and product-based acquisition, S^1) has a different set of associated saccade probabilities $P(a_{i,t} \mid a_{i,t-1})$ and $P(p_{i,t} \mid p_{i,t-1})$.

For state 1 of the middle layer ($S^1 = 1$) we impose a structure on the saccade probabilities between products that allows for eye movements that are mostly, but not necessarily, consistent with strict attribute-based acquisition. We assume that at any time the eyes have a probability p of continuing to move from one product to another along the same attribute, with probability $P(p_{i,t} \mid p_{i,t-1})$. These are eye movements consistent with an attribute-based acquisition strategy. But, with a small probability $(1-p)$ the participant may also make elementary eye

16

movements that are inconsistent with that strategy (types 2 and 3). In the product-based

acquisition state (S^1=2) the eyes have a probability q of moving from one attribute to the other

along the same product, with probability $P(a_{i,t} \mid a_{i,t-1})$. This is an eye movement consistent with

product-based acquisition. The eyes, however, also have a small probability of $(1-q)$ of making

inconsistent moves (types 1 and 3). This formulation renders the model conservative in its

identification of switching between the underlying acquisition strategies, because it allows eye

movements to deviate from strict attribute-based and product-based acquisition strategies. These

assumptions yield the following set of equations for the lower-level saccade probabilities:

$$
\begin{aligned}
P_{S^1=1}(y_{i,t} \mid y_{i,t-1}) &= P(p_{i,t} \mid p_{i,t-1}) \cdot (1-p) && \text{iff } a_{i,t} \neq a_{i,t-1} \\
P_{S^1=1}(y_{i,t} \mid y_{i,t-1}) &= P(p_{i,t} \mid p_{i,t-1}) \cdot p && \text{iff } a_{i,t} = a_{i,t-1} \\
P_{S^1=2}(y_{i,t} \mid y_{i,t-1}) &= P(a_{i,t} \mid a_{i,t-1}) \cdot (1-q) && \text{iff } p_{i,t} \neq p_{i,t-1} \\
P_{S^1=2}(y_{i,t} \mid y_{i,t-1}) &= P(a_{i,t} \mid a_{i,t-1}) \cdot q && \text{iff } p_{i,t} = p_{i,t-1}
\end{aligned}
\tag{1}
$$

Because we are interested in the extent to which attribute-based and product-based

information acquisition is local (on contiguous cells), or global (on noncontiguous cells) (Liechty

et al. 2003), we re-parameterize the attribute saccade probabilities $P(a_{i,t} \mid a_{i,t-1})$, and the product

saccade probabilities $P(p_{i,t} \mid p_{i,t-1})$, as probabilities on spatially contiguous versus spatially

noncontiguous attributes and products.

The switching between the attribute-based and product-based states of the middle layer

(S^1=1,2) follow a Markov process that is governed by the upper-layer hidden states (S^2) (see

Figure 2.2). These upper layer states can be conceived of as regimes that govern the middle layer

switching patterns. Given an upper layer state (S^2), the transitions among middle layer hidden

states (S^1) follow a Markov process with a transition probability matrix $\Pi_{S^2}(S^1_{i,t} \mid S^1_{i,t-1})$. That is,

the upper-layer state influences how participants switch between the attribute-based and product-

17

based (middle layer) states. The transitions between the upper-layer hidden states (S^2) also follow a Markov process described by the transition probability matrix $\Omega(S^2_{i,t} \mid S^2_{i,t-1})$. While the number of states of the middle layer is dictated to equal two by theory (attribute-based and product-based acquisition), the number of states of the upper layer is a-priori unknown.

We can now write the saccade probabilities between cells of the comparison matrix, $y_{i,t} \mid y_{i,t-1}$, conditional on the states of the two hidden layers that participant i is in at fixation t, $S^1_{i,t}$ and $S^2_{i,t}$, as:

$$P(y_{i,t} \mid y_{i,t-1}; S^1_{i,t}, S^2_{i,t}) = \sum_{S^2_{i,t-1}=1}^{M} \Omega(S^2_{i,t} \mid S^2_{i,t-1}) \sum_{S^1_{i,t-1}=1}^{N} \Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1}) P(y_{i,t} \mid y_{i,t-1}) \tag{2}$$

with $P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1})$ given by (1). If Θ collects all parameters, and $P_{S^1_{i,t}}(y_{i,1})$ is the initial fixation probability, the likelihood function of participant i is:

$$L(y_i \mid \Theta) = P_{S^1_{i,1}}(y_{i,1}) \prod_{t=2}^{T} \sum_{S^2_{i,t}=1}^{M} \cdots \sum_{S^2_{i,T}=1}^{M} \left[\sum_{S^1_{i,t}=1}^{N} \cdots \sum_{S^1_{i,T}=1}^{N} \prod_{t=2}^{T} \Omega(S^2_{i,t} \mid S^2_{i,t-1}) \sum_{S^1_{i,t-1}=1}^{N} \Pi_{S^2_{i,t}}(S^1_{i,t} \mid S^1_{i,t-1}) P_{S^1_{i,t}}(y_{i,t} \mid y_{i,t-1}) \right] \tag{3}$$

A key output of the model estimation is the marginal posterior probability that participant i is in information acquisition state $S^1_{i,t}$ at fixation t: $P(S^1_{i,t} \mid y_{i,t}, \Theta)$, as well as the posterior probabilities of being in the upper level states $S^2_{i,t}$: $P(S^2_{i,t} \mid y_{i,t}, \Theta)$. Those probabilities allow us to describe the information acquisition strategies that participants use from moment-to-moment.

2.3.3 Model Estimation and Testing

We specify uninformative conjugate priors on all model parameters. We use MCMC to estimate the model, which is programmed in R. Single move sampling schemes are used to sample middle layer hidden states S^1, upper layer hidden states S^2, and the parameters of the transition matrices (Robert, Celeux, and Diebolt 1993). Several tests on simulated data reveal

accurate recovery of the parameters[3]. In all analyses, we apply the model using 25,000 draws and discard the first 5,000 draw to burn-in. The chains are stabilized after 5,000 draws. We take one in ten target draws and report the mean and standard deviation of the resulting 2,000 draws to summarize the posterior distributions of the parameters.

We compare our model with realistic alternatives described later, and test for the number of upper layer states of our model using the log-marginal density (LMD). We compute the LMD using Chib's (1995) method, which provides unbiased and stable estimates:

$$LMD(Y) = In\ f\ (Y\ |\ \Theta^*) + In\ \pi(\Theta^*) - In\ \pi(\Theta^*\ |\ Y) \qquad (4)$$

The calculation of $In\ \pi(\Theta^*)$, the log-prior density, and $In\ \pi(\Theta^*\ |\ Y)$, the log posterior density, both computed at the ordinate of the posterior density Θ^* (for example, the posterior mean) is straightforward. We compute the high-dimensional sum in the likelihood (3) using Scott's (2002) likelihood recursion method.

2.4 Information Acquisition on A Comparison Website

2.4.1 Experimental Procedure

We chose the Dell website (www.Dell.com) as context for our study. It provides the option of comparing various personal computers that are relevant for our participants. We manipulate the display format by transposing rows and columns in a two-group design. The original comparison matrix that we singled-out from the website contains twelve attributes: 'Picture', 'Price', 'Processor', 'Operating System', 'Memory', 'Keyboard Mouse', 'Monitor', 'Hard Drive', 'Optical Drive', 'Wireless', 'Office Software' and 'Warranty'; and four desktop models: 'Inspiron 864', 'Inspiron 819', 'Inspiron 758' and 'Inspiron 689'. The comparison

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[3] 30 participants each with 100 observations, transition matrix with 3 columns or 3 rows. All true values fall within the 95% Highest Posterior Density region of the parameters in question; details available upon request.

matrix thus lists twelve attributes in the rows, and four desktop products in the columns, plus one column that contains attribute labels. In the second condition, the comparison matrix is transposed, so that the attributes are in columns and products in rows. We label the two conditions as the Product-Column (PC) and the Product-Row (PR) condition, respectively. 108 undergraduate students (55 male) for which choice of a personal computer is relevant participated. Participants were randomly assigned to either the PC or the PR condition. They read the instructions that asked them to make a choice for a desktop computer. After having made their final choice, they were asked to indicate how easy it was to collection information and decide among the different computers on a 5-point response scale.

2.4.2 Eye movement Recording

Tobii 1750 infrared eye tracking equipment was used (www.Tobii.com). It leaves participants free to move their heads; cameras in the rim of a LCD-computer monitor (1,280 x 768 pixel resolutions) track the position of the eye and head. Measurements are taken with a frequency of 35Hz and a precision better than 0.5 degree of visual angle. Instructions and stimuli were presented on the monitor and participants continued to a next page by pressing the space bar. Saccades between cells of the comparison website (a total of 18,172 observations) are the unit-of-analysis; re-fixations were excluded.

2.5 Results

2.5.1 Model Comparisons

We compare the proposed model with four alternatives. Alternative model 1 is a HMM without the upper layer but else is the same as our proposed model. If this model would be the best, the probabilities of switching between attribute-based and product-based information

20

acquisition (level 2) would be constant over time. It would imply that a single stage rather than a two- or multi-stage decision process (Bettman et al. 1998) would direct information acquisition in the present context. Alternative model 2 is a two-layer HMM without the (level 2) constraints of attribute-based and product-based acquisition processes. If this model would be the best, it would imply that eye movements do not reflect the two information acquisition strategies. Finally, we test for 2, 3 and 4 upper-layer hidden states for our model. We perform all these tests for both PC and PR formats.

Our model with 2, 3 or 4 upper layer hidden states outperforms both alternative HMM models, as revealed by the higher LMDs in Table 2.1. This holds for both conditions (PC and PR). These results provide support for the hierarchical structure of the decision process: a three-layer model explains the decision process better than a two-layer model. As shown in Table 2.1, the value of the LMD levels off after three upper-level states. In addition, the parameter estimates of two hidden states in the 4-state model are quite similar. Thus, we choose the model with three upper-layer hidden states as our final model.

[INSERT TABLE 2.1 ABOUT HERE]

2.5.2 General Estimation Results

Appendices I and II provide the parameter estimates of the model. Table 2.2 presents, for the PC and PR conditions, the probabilities that saccades are consistent with attribute-based, or with product-based acquisition. For the PC presentation format, in the attribute-based state participants are 14.0 times more likely (calculated as $p/(1-p)$) to move their eyes within the same attribute than making other eye movements. For the PR format this ratio drops to 8.1. For the PC format, in the product-based state participants are 1.7 times more likely (calculated as $q/(1-q)$) to make an eye movement within the same product than making other eye movements. For the PR

21

format this ratio increases to 2.8. Two conclusions are apparent. First, the eyes are much more consistent in moving across products for the same attribute, regardless of whether the products are presented in the rows or columns. Second, consistency is substantially higher for either acquisition strategies if it is presented row-wise. This corroborates previous findings on the dominance of horizontal eye movements in very different research areas (Gilchrist and Harvey 2006, Van der Lans et al. 2008, Tatler and Vincent 2008).

Table 2.2 also shows for the PC and PR conditions the probabilities that participants make contiguous and non-contiguous eye movements. For the PC format, eye movements between contiguous attributes are 10.1 times more likely than between non-contiguous ones. This ratio is 8.2 for the PR format. For contiguous/non-contiguous products that ratio is 2.6 for the PC, and 1.8 for the PR format. Participants are much more likely to compare information from neighboring attributes than from neighboring products, regardless of the orientation of the display. And they are even more likely to do so when attributes are presented in the rows (PC format). The PR format induces less contiguous information acquisition than the PC format. This dominance of information acquisition on contiguous cells of the matrix is in line with prior accounts of the dominance of local eye movement patterns in print advertisements. Yet, it seems not to have been reported in previous research on decision making on product-attribute displays where the information content rather than placement is expected to exert stronger impact in comparison and evaluation. These results provide evidence for mostly local information acquisition interspersed by short periods of redirecting the attentional spotlight to other potentially informative regions, with some influence of the presentation format.

[INSERT TABLE 2.2 HERE]

We describe the attribute-based and product-based states of the middle layer in more detail. First, when being in the attribute-based state, the average number of products inspected within an attribute is a little over two (2.28 in the PC and 2.07 in the PR condition), while one to two attributes are inspected (1.55 in the PC and 1.38 in the PR condition)[4]. Second, when being in the product-based state, the average number of attributes inspected within a product is about three (3.11 in the PC and 3.20 in the PR condition), while on average about a single product is inspected (1.04 in both conditions). Thus, participants inspect about three attributes for a single product, or compare two products on one to two attributes, before switching to another strategy of processing. This is largely independent of the orientation of the display.

Figure 4 plots the cumulative percentages of attributes and products inspected across the (normalized) decision time. In both formats, participants do not examine all products until about halfway through the decision process. The increase in the number of attributes inspected with increasing decision time is almost linear, with around half of the attributes (51% in the PC and 46% in the PR condition) inspected halfway through. About twenty percent of the attributes (25% in the PR condition and 17% in the PC condition) are never inspected. Both the number of attributes and the number of products inspected are lower in the PR than in the PC condition. This selectivity in information acquisition may be due to information overload that limits the uptake of available information, and is influenced by the presentation format.

[INSERT FIGURE 4 ABOUT HERE]

Appendix I provides estimation results for the middle and upper layers of the model. The upper layer states in the model govern the prevalence of the middle layer states and the switching between them. Although it is not always possible or advisable to interpret these upper level states

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[4] The average number of products inspected is somewhat lower at the beginning and end of the decision process (about 1.7 on average).

and one may merely view them as a flexible approximation to the time-structure in the data, they are clearly differentiated in the present application. That is, upper-layer state $S^2=1$ induces state-dependence with participants having a large probability of sticking to whatever their current acquisition strategy is (a "stay" regime). State $S^2=2$ induces switching to and staying with attribute-based acquisition (a "switch to and stay with attribute" regime). State $S^2=3$ induces switching to and staying with product-based acquisition (a "switch to and stay with product" regime"). This interpretation holds for both formats.

Figure 5a presents the (posterior) probabilities of the three upper layer states ("regimes") across (normalized) time for all participants; Figure 5b graphs the probabilities of the two middle layer states ("acquisition strategies"). Counter to theories of two-stage decision making that postulate a long period of attribute-based acquisition in the first stage followed by a long-period of product-based acquisition in the second stage, Figure 5a shows that in both formats, "switching to and staying with attribute-based acquisition" ($S^2=2$) dominates in the middle part of the decision process, and that "switching to and staying with product-based acquisition" ($S^2=3$) dominates in the early and later parts of the process. In addition, upper-layer state $S^2=1$ ("stay") is more prevalent in the beginning and the end, which indicates that participants are then less likely to switch between strategies. Saccade lengths (calculated as the Euclidean distance between the corresponding cells of the comparison matrix) are much larger for state 1 ($S^2=1$) (35.4) than that for states 2 ($S^2=2$) and 3 ($S^2=3$) (12.2 and 7.8 respectively). This suggests that, independent of the format, participants tend to adopt a more global product-based information acquisition in the beginning and end of the decision process. The prevalence and stickiness of product-based strategies towards the end of the decision process in particular, is consistent with a

pre-decisional gaze bias that reflects a cascading preference formation and decision justification (Pieters and Warlop 1999; Shimojo, Simion, Shimojo, and Scheier 2003).

As for the format impact, Figure 5a shows that for the PR format, the prevalence of the upper-layer state 3, which induces "switching to and staying with product-based acquisition", is much higher than that for the PC format. In the latter format, upper-layer state 2, inducing "switching to and staying with attribute-based acquisition", dominates. Thus, the PR format indeed induces more product-based acquisition (Bettman and Kakkar 1977). This is confirmed in Figure 5b, which shows the prevalence of the two middle layer states over time. The figure shows, however, that this dominance of product-based acquisition in the PR format manifests itself only in the middle of the decision process. For the PC format, product-based and attribute-based acquisitions are equally prevalent in the mid-range of the decision. The dominance of product-based acquisition at the beginning and end of the decision process is unaffected by the information display format.

A multinomial logit model with the total (posterior mean) durations of different acquisition states as predictors (pseudo-R^2 = .821), shows that more attribute-based acquisition significantly increases the probability of choosing product 1 over 4 ($b = 6.32$, $p = .003$), while it reduces that of the other products ($b = -7.01$ for product 2, $p = .001$, -6.33 for product 3, $p = .063$). Product 1 (Inspiron 864) is superior on most non-price attributes. Thus, participants in the PC condition seem more likely to choose the dominating product than those in PR condition (choice probabilities: PC: .26 *vs*. PR: .20). They also seem less likely to choose the second product (choice probabilities: PC: .08 *vs*. PR: .13), which is inferior on most non-price attributes.

[INSERT FIGURE 2.5 ABOUT HERE]

25

2.5.3 Switching between Information Acquisition Strategies

To illustrate the switching between information acquisition states, Figure 6 plots their probabilities over time for one illustrative participant in the PC and one in the PR condition. The Figure shows that switching between the two (middle-layer) information acquisition strategies is very frequent, but for the PR format even more so. On average, participants switch respectively .61 and .83 times per second for the PC and PR conditions. If we were to count single-step transitions in the eye movements directly, we obtain even higher switching frequencies: 1.27 (PC) and 1.37 (PR) switches per second. These latter observed frequencies are much higher, because eye movements are equated with information strategies, rather than being treated as noisy indicators of them. But, even though our model provides much more conservative estimates, switching between the two information acquisition strategies is so frequent that it is unlikely that these reflect conscious "strategies", and we will call them "modes" instead.

[INSERT FIGURE 2.6 ABOUT HERE]

Participants switch between the upper layer states .84 times per second for the PC condition and .88 times for the PR condition. Thus, while the presentation format affects the switching between the states of the middle-layer (modes of information processing), it does not affect switching between the upper-layer states. These states might be associated with higher cognitive processes (Salvucci and Anderson 1998), which may be less susceptible to bottom-up influences such as the presentation format.

This frequent switching between acquisition modes significantly increases decision time (regression coefficient $b = 1.53$ for middle layer switching, $p = .06$; $b = 2.30$ for upper layer switching, $p < .001$). Further, switching significantly reduces the experienced ease-of-processing (average of post-choice evaluation items, $M = 2.78$; $b = -.33$ for middle-layer switching, $p =$

.002). Therefore, participants perceive the decision process to be easier in the PC condition (less switching) than that in the PR condition ($M = 3.02$ and $M = 2.64$ respectively; $p = .059$).

To investigate determinants of switching between states, we estimate logit regressions of the participant-specific switching indicators on the percentages of products (P), respectively attributes (A) inspected up to that time point. In the middle-layer, switching from product-based to attribute-based acquisition is predicted by the percentage of attributes already inspected (PC condition: $b= .29$; $p=.08$; PR condition: $b= .38$, $p=.07$). Switching from attribute-based to product-based acquisition, on the other hand, is predicted by the percentage of products already inspected (PC condition: $b= .48$, $p=.03$; PR condition: $b=.96$, $p<.001$). This corroborates that participants switch to a specific mode of information acquisition as more information has been acquired in the other mode (Russo and Rosen 1975; Bettman and Park 1980).

2.5.4 Attention to Products and Attributes

Next we show what specific product and attribute information consumers acquire over time when they are in respectively the attribute-based and product-based acquisition states. For that purpose we select three participants representative for the PC and the PR conditions, by K-means clustering participants based on their fixations on products and attributes, and selecting the most central participant for each cluster. The cumulative numbers of fixations on products in the attribute-based state and on attributes in the product-based state are shown in Figures 7 (PC condition) and 8 (PR condition), respectively. The number and pattern of fixations that the products and attributes receive shows considerable heterogeneity between participants, but four key insights can be obtained.

First, in many cases, some products seem to be taken out of consideration and receive no additional gaze after a certain time point: the cumulative product-fixations in the attribute-based

27

state level off, even more so for the PR than for the PC format. This is in line with theories of hybrid decision-making (Bettman 1979). However, contrary to those theories, in several cases the eliminated alternative is reconsidered later in the decision process. Take product 1 (Inspiron 864) in the left bottom of figure 7c as an example. The product receives constant attention at first, then cumulative fixations level off while the other two or three products are compared. At a later stage of decision-making (after a wait of about 25 fixations), however, this product is being considered again, as reflected by increasing fixations. It might be that product 1 is being "put on hold" while other alternatives are compared, or, it is possible that this product is taken out of consideration at first and then is being re-considered later. Either way, it seems that the comparison set changes over the entire time course of decision making. Indeed, the scope of the product comparison set shrinks and expands (between 1 and 4, SD = 1.10). Thus, in contrast with hybrid decision-making theories that postulate that the comparison set is constant after a certain time point, the plots show that it changes over time.

Second, in the product-based acquisition state, attributes enter the decision process sequentially. Many are considered only once. The temporal sequence of selection of attributes may reflect their relative importance to the choice goal at hand (Bettman et al. 1998, Wedell and Senter 1997). It seems that for each of the representative respondents a fair number of attributes is not considered at all, which is even more so in the PR condition.

Third, regularly attributes and products that have been rejected earlier are briefly revisited in the final stage of the decision process. This appears to reflect a final verification of the alternative to which the participant has committed (Russo and LeClerc 1994; Russo and Rosen 1975). A few attributes appear to be exclusively used in this final stage of the decision.

28

Fourth, in the majority of the cases there is a very clear pre-decisional acceleration of gaze on the chosen alternative towards the end of the decision. This gaze cascade is predictive of the alternative that is chosen (Pieters and Warlop 1999; Glaholt and Reingold 2009; Shimojo et al. 2003).

[INSERT FIGURES 2.7 AND 2.8 ABOUT HERE]

2.6. Discussion

Decision theorists have argued that eye tracking provides insights into fast and partly automatic information acquisition processes during decision making. In recent years affordable and easy to use eye tracking equipment has become widely available. With that, the challenge has become to describe the large volumes of data that eye tracking studies produce in a meaningful manner. For this purpose, the proposed Hierarchical Hidden Markov Model (HHMM) can help. In our study we apply the HHMM to eye tracking data to describe moment-to-moment information acquisition on product-by-attribute matrices.

This revealed that participants switch frequently between product-based and attribute-based acquisition modes: 50 to 60 times during the 67 seconds that a decision took, on average. The amount of information already collected on attributes induces switching away from the by-product mode, and the amount of information on products induces switching away from the by-attribute mode. This high degree of switching during real-life decision making has not been documented previously, and its causes are not fully understood. Participants limit their attention to about three attributes for a single product, or two products for one to two attributes. This might be due to the restricted rate at which information can be consolidated (Marois and Ivanoff 2005), and limits on the amount of information that can be stored into visual short term memory at a particular point in time (Cowan 2001, Luck and Vogel 1997). Instead of sequentially

29

adopting attribute-based acquisition to eliminate alternatives followed by product-based acquisition, participants appear to sample "parcels" of attribute and product information (Stewart, Chater, and Brown 2006). They constantly adjust their acquisition mode and the comparison set of products to consolidate information into memory and make the next information acquisition decision. Investigating the causes and effects of information parceling and acquisition mode switching may be an avenue for future research.

The revealed high frequency of switching cast doubts on whether "by-attribute" and "by-product" information acquisition strategies are conscious and deliberate strategies. Rather, presentation format, but also low-level eye movement tendencies that could not be incorporated in previous accounts of decision making, appear to play an important role. Low-level, automatic and unconscious processes are principal in situations of information overload and time pressure (Lee and Lee 2004; Pieters and Warlop 1999), which occur when facing data-rich web-based choice environments. First, there is a predominant left-to-right tendency in the eye movements that makes it appear as if there is a "by-product" or "by-attribute" strategy of processing, depending on the orientation of the matrix display. Second, information acquisition is predominantly local, confined to neighboring cells on the display, because of limited visual detail beyond the immediate eye fixation point. Third, the end of the decision process reveals a pre-decisional gaze bias that reflects a cascaded process of preference formation and is predictive of the final choice. In our study the presentation format impacts the way that information is acquired, because the format changes but the low-level eye movement tendencies (left-right, local) do not. If eye movement patterns stay the same when the information display changes, then this causes different information to be extracted and different decisions to be made. This makes information acquisition and decision making seem adaptive, while in fact they are not.

Instead of purposely using attribute-based and product-based "strategies", participants tend to use a strategy of local information sampling, and tend to make horizontal movements. Information placed contiguously is likely to exert a strong impact on decisions. Such tendencies provide opportunities for managers to strategically place product-attribute information to facilitate comparisons. For example, one could increase the attractiveness of a specific product by placing it next to a product that it dominates overall, or on specific attributes (Huber, Payne, and Puto 1982). Comparison website providers can also adopt display formats in a proactive fashion to stimulate consumers' use of specific information acquisition mode favorable to their goals. Managers need to decide how to balance format, sales objective, and switching cost. For example, we find that that the Product-Column format facilitates attributed-based acquisition and increases the chance of the dominant product being chosen. Product-Row format leads to more evenly distributed choice probabilities. However, the Product-Row format favors by-product information acquisition, which results in more local eye movements, less products and attributes being inspected, and increased switching between modes of acquisition that makes choice more difficult. Some comparison websites (e.g., Nextag.com) now allow consumers to firstly sort alternatives by certain attribute, such as price, ratings, etc., and then present the sorted product information in Product-Row format (by default). This may be in conflict with desirable attribute-based information processing for these websites and make decision making more difficult.

Comparison websites, the context chosen for the present research, are a relatively new shopping environment, yet rapidly increasing in popularity. We demonstrated the effects of the row-column orientation of the website, as a useful starting point for research in this area. With the advance of network engineering, comparison websites are now able to provide more and more extensive and dynamic product-attribute comparisons. Website designers therefore have

31

increasing abilities to improve comparison website usability and may use the results of this study to help induce information acquisition modes that are congruent with their goals. We hope that our study stimulates further research interest in this area, which could include the influence of website design factors such as sorting (arranging the product order such that it reflects relative importance), grouping (placing similar or related elements close together), trimming (eliminating unnecessary information), and highlighting (visually accentuating important information through colors and shading). According to Johnson et al. (2008) decision research can progress more quickly when it adopts approaches that provide richer descriptions of the underlying processes. Our proposed Hierarchical Hidden Markov model may provide a starting point for the development of such models of online choice.

Table 2.1   Log Marginal Density (LMD) of Alternative Models

| Experimental Condition	Proposed HHMM Model with *n* States in the Upper Layer			Alternative Model 1: Constrained HMM	Alternative Model 2: Unconstrained HMM
	Two States	Three States	Four States		
Product-column	-10392.00	-9066.07	-9058.13	-13696.97	-13132.81
Product-row	-10877.76	-9503.57	-9484.53	-13168.99	-12205.66

Table 2.2   Parameter Estimates For Eye movements (lower layer) and Information Acquisition Strategies (middle layer) (with standard deviations in parentheses)

Acquisition Strategy (Middle Layer)	Components	Information Presentation Format	
		Product-Column	Product-Row
Attribute-based	Consistent	.929 (.001)	.892 (.001)
	Inconsistent	.066 (.022)	.110 (.011)
	Contiguous (products)	.444 (.007)	.283 (.006)
	Noncontiguous (products)	.171 (.009)	.157 (.007)
Product-based	Consistent	.641 (.005)	.736 (.002)
	Inconsistent	.360 (.016)	.264 (.008)
	Contiguous (attributes)	.362 (.000)	.338 (.002)
	Noncontiguous (attributes)	.036 (.001)	.041 (.000)

Note: "Consistent" is the probability of staying in the same attribute or product (*p* or *q*), "Inconsistent" is the probability of moving to another attribute or product (1-*p* or 1-*q*). "Contiguous" is the average of the transition probabilities between block-diagonal sub-matrices (all elements on the 2×2 diagonal blocks, see Appendix II, shadowed parts), "Noncontiguous" is the average transition probabilities between the cells in the off-diagonal blocks (all elements except those in the diagonal blocks)

Figure 2.1   Eye Movements of A Single Participant Making A Choice on the Dell Comparison Website.

Circles indicate eye fixations (with fixation numbers), and lines indicate saccades between fixations.
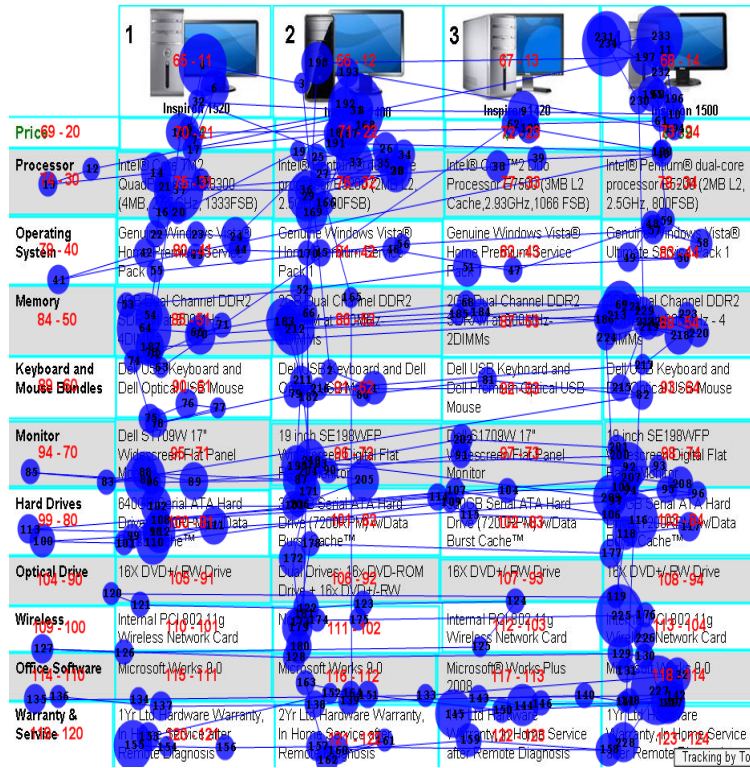
Figure 2.2   The Three Layers of the Proposed Hierarchical Hidden Markov Model
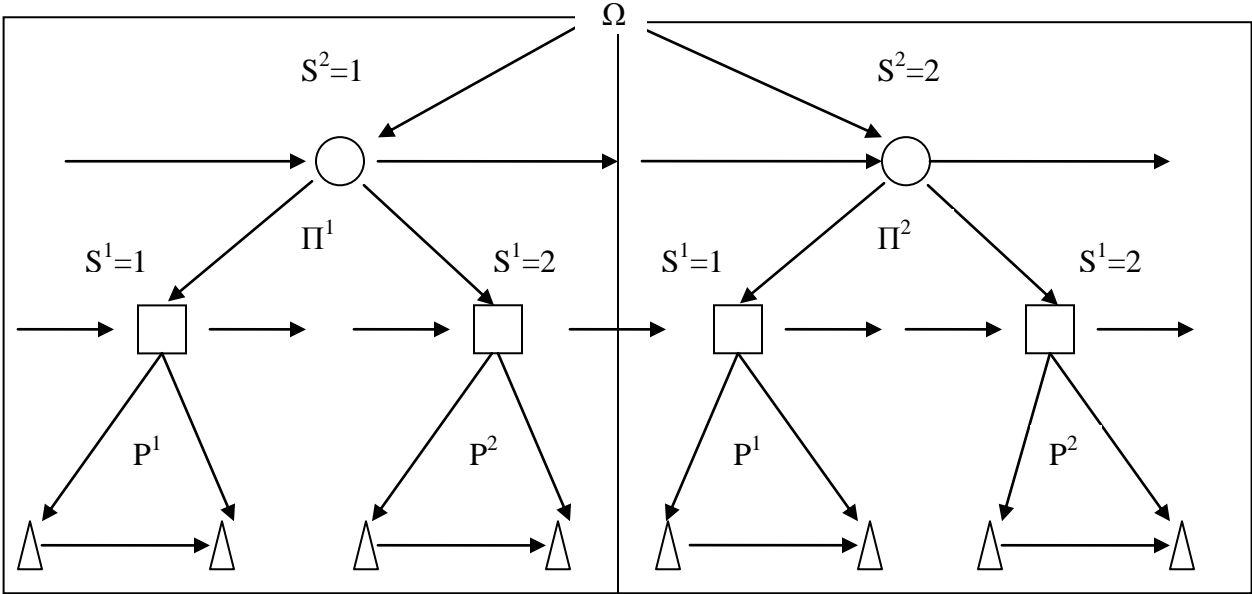
Note: Triangles represent the observations in the lower layer, with transition probabilities P^1 or P^2; squares represent the hidden states in the middle layer (S^1), with transition probabilities Π^1 and Π^2; circles represent the hidden states in the upper layer (S^2), with transition probability Ω.

Figure 2.3   Product-Attribute Matrix: Information Acquisition Strategies and Elementary Eye Movements
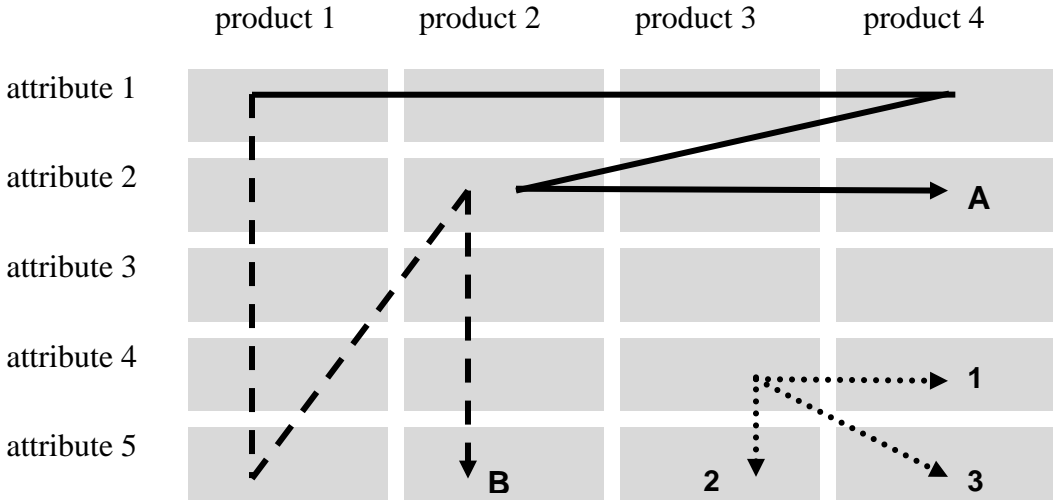
Note: Elementary eye movements (dotted arrows): type 1 is saccade between two attributes of same product, type 2 is saccade between two products within same attribute, and type 3 is saccade from one attribute of a product to another attribute of another product. Arrow A is attribute-based acquisition and comprises type 1 and 3 movements. Arrow B is product-based acquisition and comprises type 2 and 3 movements.

Figure 2.4   Cumulative Percentage of Attributes and Products Inspected across (normalized) Decision Time for Product-Column (PC) and Product-Row (PR) Conditions.

X-axis: normalized decision time; Y-axis: cumulative percentage of attributes and products inspected
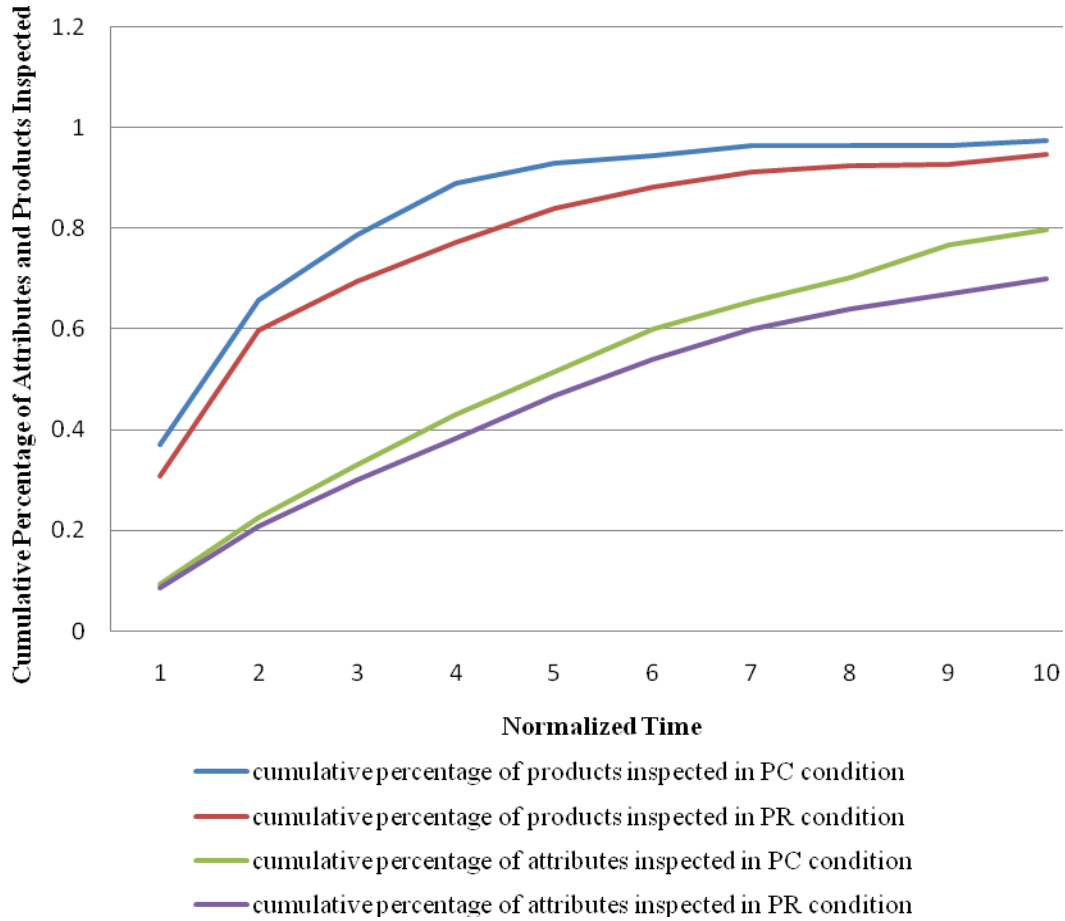
Figure 5a   **Aggregate Time Course of the Prevalence of Upper Layer States: S2=1 (long dash), S^2=2 (short dash) and S^2=3 (solid line) for Two Information Presentation Formats**
X-axis: normalized decision time; Y-axis: probabilities of three upper layer states

Product-Column Format   **Product-Row Format**
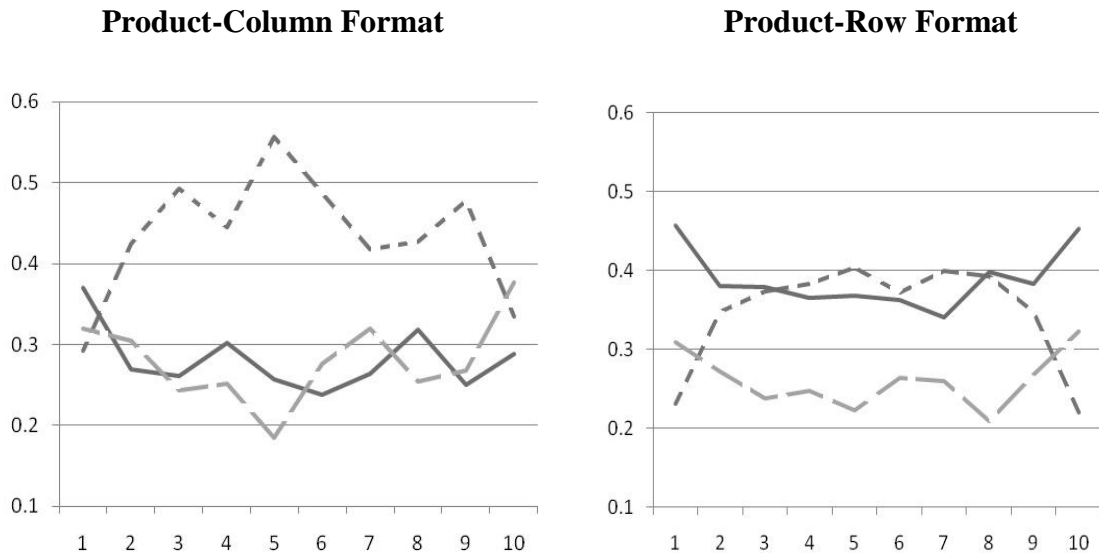
Figure 5b   **Aggregate Time Course of Attribute-Based (short dash) and Product-Based (solid line) Information Acquisition for the Two Information Presentation Formats**
X-axis: normalized decision time; Y-axis: probabilities of two middle layer states

Product-Column Format   **Product-Row Format**

38
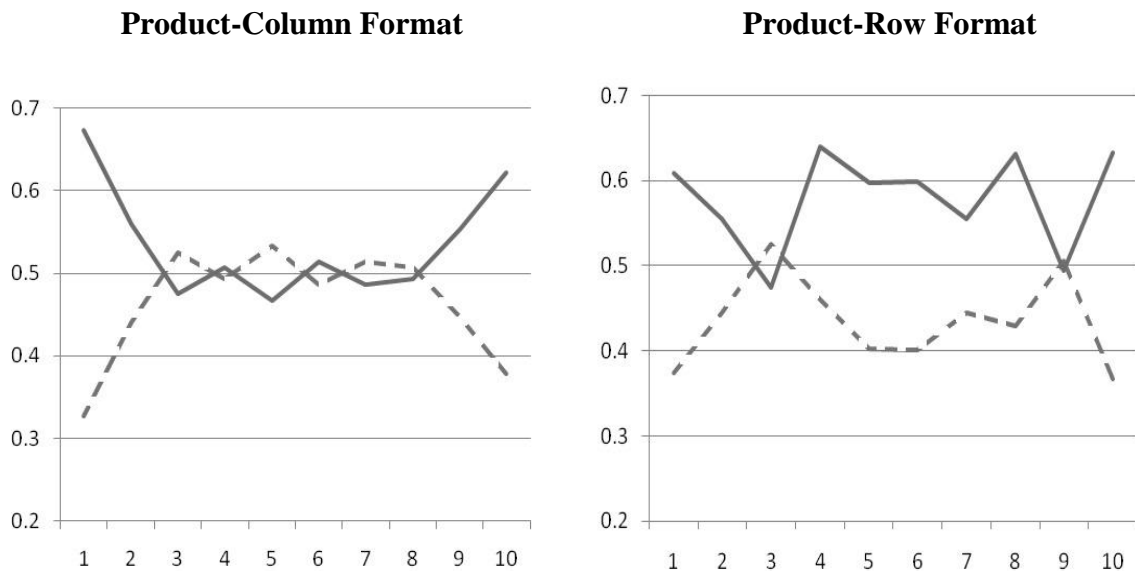
Figure 2.6 **Examples of the Time Course of the Three Upper-Layer States (S^2=1: long dash, S^2=2: short dash and S^2=3: solid line), and of the Two Middle Layer States (attribute-based acquisition: short dash, and product-based acquisition: solid line), for One Participant in Each Condition (presentation format)**

X-axis: fixation number; Y-axis: probabilities of each state in the middle and upper layers

Product-Column Condition
(Participant 17)

Upper Layer

Middle Layer

Product-Row Condition
(Participant 3)

Upper Layer
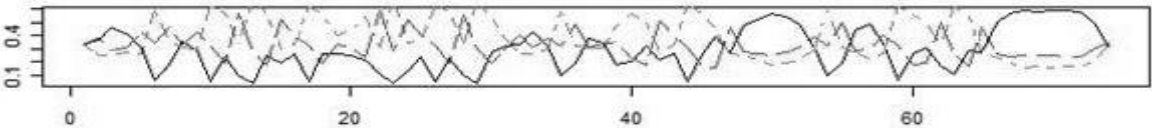
Middle Layer
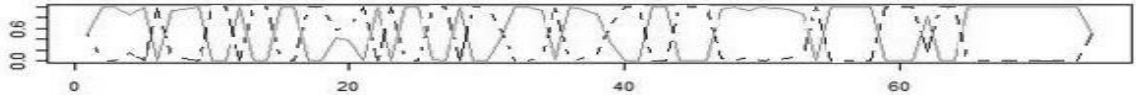
Figure 2.7a   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 39, PC condition. Chosen Alternative: 2 (Dell 819), Decision Time: 1 min and 57 sec.

X-axis: fixation number; Y-axis: cumulative number of fixations
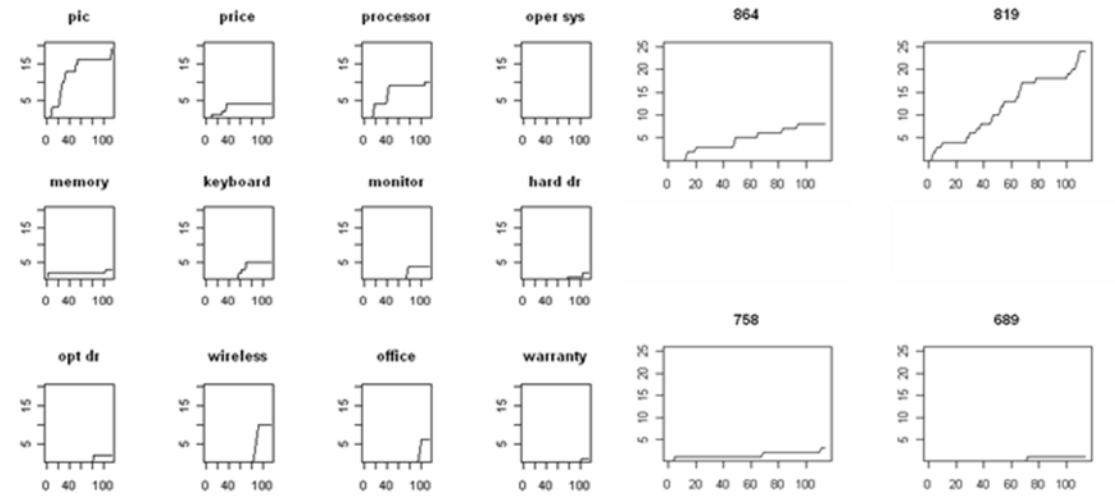
Figure 7b   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 42, PC condition. Chosen Alternative: 4 (Dell 689), Decision Time: 2 min and 8 sec.

X-axis: fixation number; Y-axis: cumulative number of fixations

40
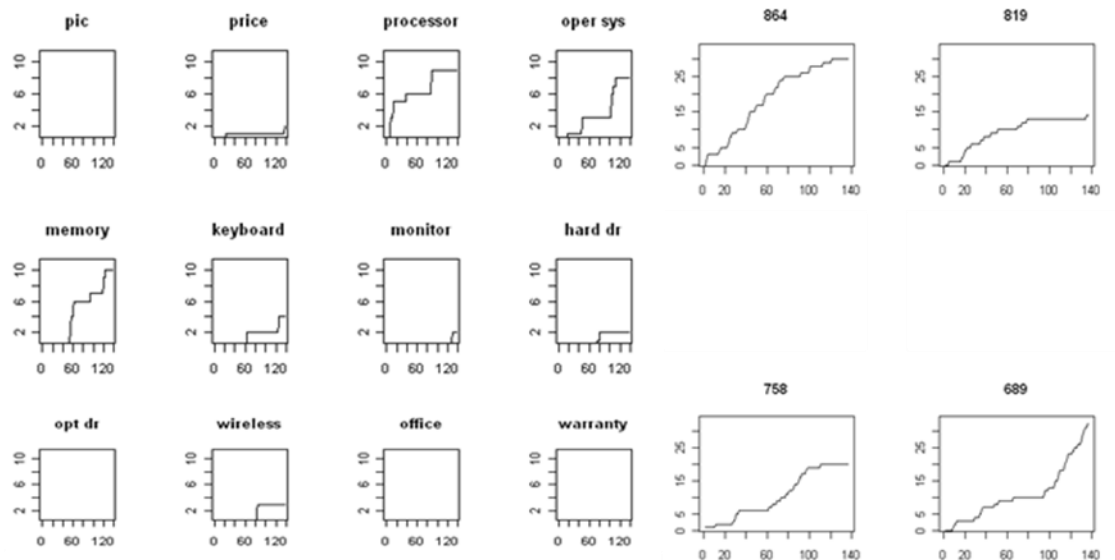
Figure 2.7c   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 19, PC condition. Chosen Alternative: 1 (Dell 864), Decision Time: 1 min and 28 sec.
X-axis: fixation number; Y-axis: cumulative number of fixations
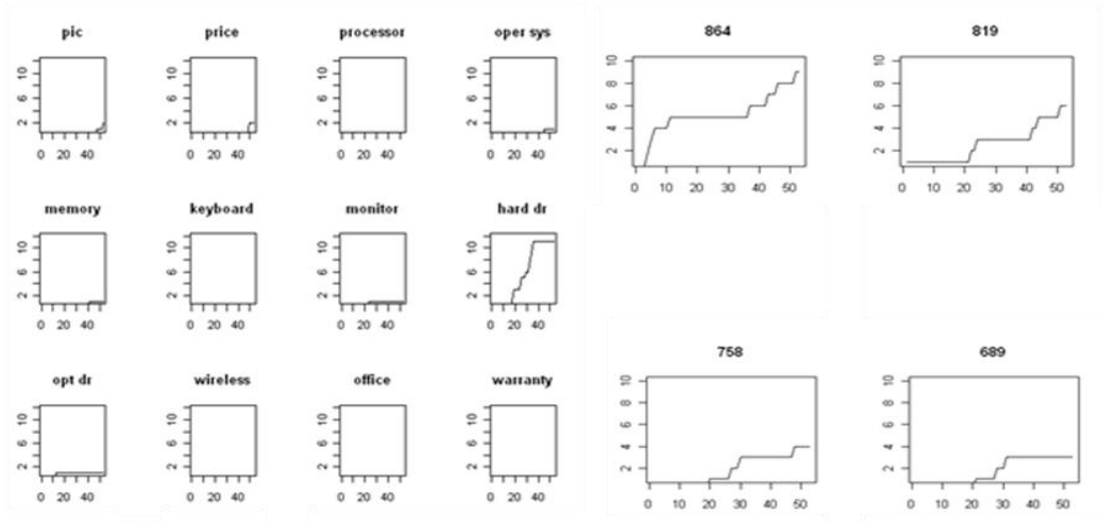
Figure 2.8a   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 24, PR condition. Chosen Alternative: 3 (Dell 758), Decision Time: 59 sec.
X-axis: fixation number; Y-axis: cumulative number of fixations
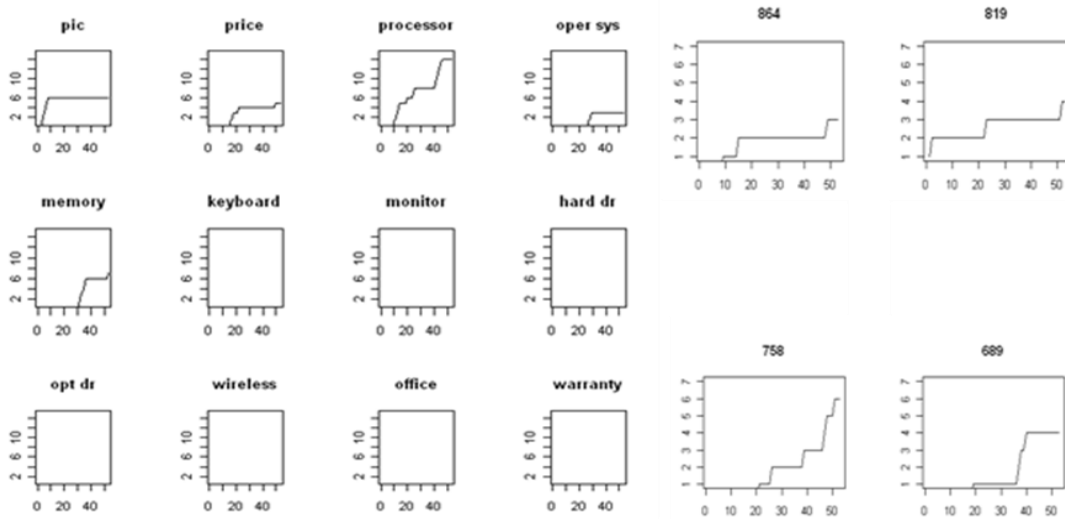
Figure 2.8b   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 22, PR condition. Chosen Alternative: 2 (Dell 819), Decision Time: 1 min and 34 sec.
X-axis: fixation number; Y-axis: cumulative number of fixations
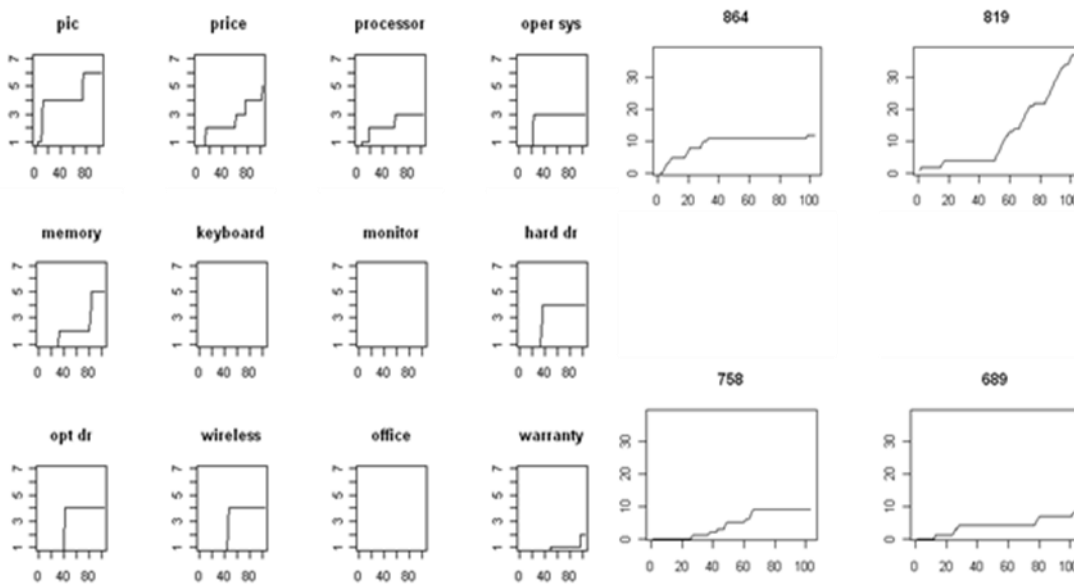
Figure 2.8c   The Cumulative Number of Fixations on the Attributes While in the Product-Based State and on the Products While In the Attribute-Based State; Participant 41, PR condition. Chosen Alternative: 3 (Dell 758), Decision Time: 3 min and 46 sec.

X-axis: fixation number; Y-axis: cumulative number of fixations
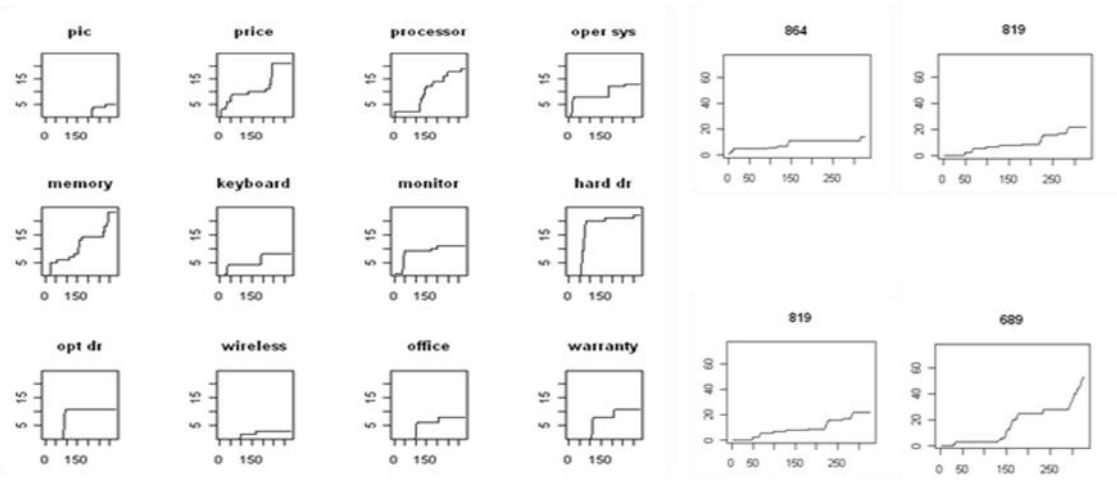
Chapter III: Usage Experience with Decision Aids and Evolution of Online Purchase Behavior

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Acknowledgments

3.1. 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 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, Wilson, and Davis 2003; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009).What is lacking in the literature is a comprehensive examination of the evolving patterns of purchase behavior, such as in terms of store loyalty and price sensitivity, and more importantly, what may drive purchase behavior changes in online stores.

It is well documented that the store environment can influence a consumer's decision making process (e.g., Park, Iyer, and Smith 1989; Inman, Winer, and Ferraro 2009). A distinct feature of the Internet store environment is that online stores offer a variety of interactive decision aids which 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 check total basket spending. Studies have shown that this kind of 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.

The objective of this research is to conduct an empirical investigation on whether and how usage experience with various decision aids may drive online purchase behavior changes over time, and what roles different types of decision aids may play in the process. We intend to address the following managerial questions: 1) Will shoppers exhibit more habitual behavior as they get accustomed to an online store, or are they more likely to engage in on-the-spot decisions as they become more experienced and efficient with using interactive decision aids? 2) How will this affect their tendency to shop from an online store and their price sensitivity? 3) What kind of decision aids can mitigate price competition? 4) What kind of decision aids may increase consumers' loyalty to an online store? and 5) How can marketers influence consumers' behavior evolvement by designs of decision aids in an online store? Answers to these questions can help Internet retailers improve the design of their store environments and provide insights for manufacturers to modify promotion messages adaptively according to consumers' evolving purchase behavior.

Online shopping behavior has been shown to be systematically different from offline shopping behavior (e.g., Danaher, Wilson, and Davis 2003; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009). For example, the observed behavioral discrepancy can be attributed to two broad sources: differences in intrinsic characteristics between online and offline consumers, and differences in the shopping environments (Zhang and Wedel 2009). Researchers have postulated that interactive decision aids available in online stores can train consumers to shop in certain fashions, which would attribute to purchase behavior differences in the two types of shopping environments (e.g., Alba et al. 1997; Degeratu et al. 2000; Zhang and Wedel 2009). Our study will provide an empirical test of this conjecture and shed light on whether decision

aids available in online stores indeed lead to purchase behavior changes for the same consumer over time.

Like the above mentioned previous studies that compare online and offline purchase behavior, our empirical investigation is carried out in the context of online grocery stores. After initial struggles and some high profile failures, Internet 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 more than 20% compound annual rate since 2003 and attracts 13 million U.S. Internet users by July 2009 (Swedowsky 2009). Findings from our study will be relevant to a wide range of companies, especially as more traditional retailers (e.g., Safeway, Albertson, Wal-Mart) and Internet retailers (e.g., Amazon.com) venture into the online grocery retailing business.

Our data are provided by a leading Internet grocery retailer which was among the very first to sell groceries online. The dataset was collected during the period when the retailer first launched its web business, which makes it particularly appealing to study the evolution of online purchase behavior. Research has shown that consumers' in-store decision making processes may vary by product categories (Inman, Winer, and Ferraro 2009). Our dataset includes detailed click-stream navigation information, as well as individual purchase history data in multiple product categories, and thus allows us to examine potential differences in the patterns across these categories.

We construct a Non-homogeneous Hidden Markov Model (NHMM) of category purchase incidence and purchase quantity, 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 this research. Shopping behavior, including

online shopping behavior, has been classified into different states, such as for "hedonic" and "utilitarian" motivations (Babin, Darden, and Griffin 1994; Childers et al. 2001; Hirschman and Holbrook 1982). These studies suggest that the observed online shopping behavior is likely to be directed by certain latent "behavior states", and the store environment may train consumers and change their behavior states over time. Our NHMM is built to identify these latent states and examine how usage experience with online decision aids may drive transitions between these states.

Understanding how consumers' purchase behavior evolves over time as their experience with decision aids accumulates would offer valuable insights for online retailers to improve the design of their store environment. It could help manufacturers modify their communication messages (for example, choose to focus on price/promotion-oriented information or to highlight specific product attributes), based on the purchase behavior revealed in different latent states. Moreover, findings from our study will suggest ways for online retailers to offer personalized shopping environment for individual consumers, or to influence their purchase behavior evolution.

3.2 Conceptual Development and Literature Review

In this section, we present the conceptual development of our study and provide an overview of the relevant literature.

3.2.1 Online Decision Aids

Online stores make the shopping process easier and more convenient by offering a variety of decision aids. These decision aids allow consumers to perform a more "thorough and exhaustive search" (Hollander and Rassuli 1999; Lee and Geistfeld 1998). They enable online

shoppers to make better purchase decisions and doing so with less effort (Häubl and Trifts 2000).
Decision aids are especially popular in online grocery stores. We classify four types of decision
aids that are commonly available in these stores.

   1. Decision aids for nutritional needs: Many online grocery stores provide decision aids
to facilitate the shopping process for consumers who have special dietary needs (Swedowsky
2009) or are concerned of nutritional information. These decision aids include sorting functions
(such as "by calories", "by cholesterol", "by sugar", and "by fat") and precluding functions (such
as "Kosher foods", "organic food only") to rank, compare, or filter the products with certain
criteria. For example, www.groceryexpres.com offers 12 functions to fulfill consumers' special
dietary needs. www.freshdirect.com has 16 such functions. Growing health concerns among the
public are believed to have contributed to the prevalence of such decision aids.

   2. Decision aids for brand preference: In online stores, consumers with specific brand
preference can choose their preferred products by the brand name using functions such as
"sorting by brand/name" or "search by (brand name)". This type of decision aids are ubiquitous
in online stores (see www.freshdirect.com, www.coles.com, www.netgrocer.com for just a few
examples). 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 www.freshdirect.com, www.safteway.com,
www.peapod.com for examples) make the shopping process easier for price-sensitive consumers.
Such decision aids facilitate price comparisons and might induce higher price sensitivity (Alba et
al. 1997). In addition, some online stores allow shoppers to check the total spending before

submitting an order, which enables budget-conscious consumers to monitor their spending more effectively during the shopping session.

     4. Personalized shopping lists: Some online stores offer consumers the option to create personal shopping lists or save previous order lists automatically (such as www.peapod.com, www.freshdirect.com, www.safeway.com, and www.walmart.com). They allow consumers who are time-constrained or have relatively consistent shopping baskets to complete the shopping process quickly. Shopping lists serve as a memory aid (Block and Morwitz 1999). Research has shown that consumers who use shopping lists tend to make less unplanned purchases (Inman et al. 2009). Therefore, usage experience with shopping lists may train consumers into habitual shoppers.

     These interactive decision aids offer online stores a unique advantage over their brick-and-mortar counterparts, by making the purchase decision process less effortful, more efficient, and more suited to individual's needs and preferences. The main objective of this study is to examine whether and how the usage experience with different types of online decision aids may drive purchase behavior changes overtime. 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.

3.2.2 Evolution of Online Shopping Behavior

     Previous studies suggest that consumers' purchase behavior may change over time in an online store (e.g., Ansari, Mela, and Neslin 2008; Zhang and Krishna 2007). In the context of offline stores and unfamiliar new product categories, Heilman and colleagues (2000) show that consumers' purchase behaviors exhibit evolving patterns as their experience with purchasing the category increases. Given that the Internet shopping environment is distinctively different from

traditional shopping channels with many unique features, shoppers new to the channel are likely

to go through learning and adaptation processes, and thus their purchase behavior may also

evolve over time.

Researchers have suggested several factors that may contribute to the evolution of online

shopping behavior over time, most of which are related to the Internet experience. For example,

comfort with the Internet (Mauldin and Arunachalam 2002), perceived ease of usage, and

perceived usefulness of online shopping all exert a positive impact on the purchase intention

from the Internet channel (Hoffman and Novak 1996; Chen, Gillenson, and Sherroll 2002;

Limayem, Khalifa, and Frini 2000; Pavlou 2003). Yet there has been little research that

empirically investigates how usage experience with various decision aids contributes to the

evolution of online purchase behavior. Our study intends to fill this void.

3.2.3 Usage Experience with Decision Aids and Online Shopping Behavior Evolution

Internet experience has been found to be an important determinant for consumers'

purchase intention at online stores (see Zhou, Dai, and Zhang 2007 for a review). Consumers

could gain Internet experience through more time spent online or repeated visits, which would

increase their comfort level with the online shopping environment and thus purchase intention

(Mauldin and Arunachalam 2002). The "comfort" may come from experience with navigating a

website or familiarity with decision aids available. Positive experience with a website may in

turn induce greater exploratory behavior on the site (Hoffman and Novak 1996; Mathwick and

Rigdon 2004). These two processes could reinforce each other and accelerate the learning of

decision aid usage. Therefore, as shoppers' experience with decision aids accumulates, their

propensity to purchase from an online store is likely to increase as well.

In terms of responsiveness to marketing mix variables, the impact of online decision aids

51

is likely to be more nuanced. We focus on price sensitivity in this discussion. Usage experience with online decision aids may affect shoppers' price sensitivities at both the store choice stage and the in-store purchase decision stage.

Many online stores allow consumers to create personal shopping lists and/or store other shopping information in their personal accounts. These decision aids could create a "lock-in" effect (Smith, Bailey, and Brynjolfsson 2000): a consumer who creates and uses personal shopping lists in one store may face higher switching costs if s/he decides to shop at other (online or offline) stores. In other words, price is not the only factor to be evaluated when determine where to shop (Bakos 2001). We expect that increased usage of personal shopping lists are likely to enhance consumers' loyalty to the store, induce habitual purchase behavior, and soften their price sensitivity when it comes to choose the shopping venue. This "lock-in" effect may also apply to other types of decision aids, such as those for nutritional needs.

The Information Integration Theory (Anderson 1971, 1981) provides some guidance in predicting the impact of decision aid usage experience on price sensitivity at the in-store purchase decision stage. According to the theory, certain attributes, such as brand or price, can surrogate information on other attributes if the latter have limited availability; yet when information on other attributes becomes available, weights of existing attributes will be reduced (Anderson 1971, 1981; Bettman, Capon, and Lutz 1975). In traditional brick-and-mortar stores, consumers are more likely to focus on price-related information because it is easily available and highly salient with frequent feature and display advertisements (Degeratu et al. 2000). In contrast, decisions aids available in online stores allow consumers to more efficiently access and utilize information on other product attributes. They now can find the product that meets their needs based on important attributes other than price at a lower search costs (Alba et al. 1997). In

other words, for some consumers, the weight of price information is likely to reduce while the importance of other attribute information is likely to increase (Degeratu et al. 2000; Smith et al. 2000), and thus price sensitivity may decrease over time as a consequence for these consumers. On the other hand, online decision aids intended for economic needs make it easier for shoppers to use price related information more efficiently. Therefore, it is also possible that, at least for some consumers, experience with online decision aids will train them to be more price sensitive (Alba et al. 1997). We leave it as an empirical question regarding the pattern of price sensitivity in online stores over time. More importantly, we intend to find out what types of decision aids may reduce price sensitivity and what types have the opposite effects.

3.2.4 Potential Hidden States of Purchase Behavior

The classification of different purchase behavior has been a long-standing research interest in the marketing literature. For instance, based on consumers' motivations for shopping, their purchase behavior can be classified into "hedonic" and "utilitarian" states (Babin et al. 1994; Childers et al. 2001; Hirschman and Holbrook 1982). Hedonic consumers are "equivalent to brick-and-mortar window shoppers for whom the shopping experience is for entertainment and enjoyment"; while utilitarian consumers (or goal-oriented shoppers) normally "purchase products in an efficient and timely manner to achieve their goals with minimum irritation" (Childers et al. 2001, p513). Cheung et al. (2003) classify online shoppers into "intention", "adoption (purchase)", and "continuation (repurchase)" types based on their purchase intentions. These different stages of purchase intentions may well apply to the same consumer over time. Heilman and colleagues (2000) conjecture that two competing forces --- consumers' desire to collect information about alternatives and their aversion to trying risky ones --- drive consumers' purchase behavior evolution among three hidden states when buying new (unfamiliar) product

categories.

In this study, we propose a Hidden Markov Model which allows us to empirically identify latent states of purchase behavior in the data. The classifications in the literature will provide valuable guidance for us to interpret these latent states.

3.3 Model Formulation

This study investigates how the usage experience with various online decision aids affects consumers' purchase behavior evolution. We construct a Non-homogeneous Hidden Markov Model (NHMM) of category purchase incidence and purchase quantity, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids.

The basic premise of our model is that consumers' purchase decisions at any given time is driven by the hidden behavior states they are in, where the hidden states differ in terms of the baseline tendency to purchase from the online store and their price sensitivity. Consumers switch between these states as their experience with decision aids accumulates over time. We adopt a Type II Tobit model (e.g., Amemiya 1984) to jointly capture category purchase incidence and purchase quantity decisions, where parameters in the Tobit model evolve according to a Hidden Markov Model (HMM) with the transition probabilities assumed to be driven by the usage experience with various decision aids. Our model belongs to the category of Non-homogeneous Hidden Markov Model (NHMM) (see Hughes 1993).

3.3.1 Type-II Tobit Model of Category Purchase Incidence and Quantity

Purchase Incidence

Let U_{it}^c = household i's latent utility of purchasing category c from the online store in

week t; $I_{it}^c = 1$ if household i purchases category c from the online store in week t, 0 otherwise.

Without losing generality, we can scale U_{it}^c such that:

$$I_{it}^c \begin{cases} = 1, & \text{if } U_{it}^c > 0 \\ = 0, & \text{otherwise} \end{cases}. \tag{1}$$

The utility function is specified as:

$$U_{it}^c = \beta^S X_t^c + \varepsilon_{it}^c, \quad \varepsilon_{it}^c \sim N(0, \delta_c^2), \tag{2}$$

where X_t^c is a vector of marketing mix variables for category c in week t. β^S is a vector of their

coefficients given that household is in hidden state s, including the intercept. The intercept can

be interpreted as a household's baseline tendency to purchase category c from the online store in

state c. In order to get clearly-defined interpretations of the hidden states, we choose to focus on

price for the marketing mix component in our empirical analysis, because price sensitivity is a

key aspect of household purchase behavior that we intend to study here. We fix $\delta_c^2 = 1$ for

identification purposes.

Purchase Quantity

Purchase quantity is observed only when a household purchases a category from the

online store. We denote Q_{it}^{c*} as household i's latent purchase quantity of category c in week t

(measured in volume units such as ounces), and Q_{it}^c as the household's observed purchase

quantity of category c in week t. Then,

$$Q_{it}^c = \begin{cases} = Q_{it}^{c*}, & \text{if } I_{it}^c = 1 \\ = 0, & \text{otherwise} \end{cases}. \tag{3}$$

We specify Q_{it}^{c*} as:

$$Q_{it}^{c*} = \phi^S Z_t^c + \upsilon_{it}^c, \quad \upsilon_{it}^c \sim N(0, \sigma_c^2), \tag{4}$$

where Z_t^c is a vector of marketing mix variables for category c in week t, and ϕ^S is a vector of their coefficients given that household is in hidden state s. Like in the purchase incidence component, we use price as the key marketing mix variable in the empirical analysis in order to get a clean interpretation of the hidden states.

We take into account the interdependence of purchase incidence and quantity decisions by assuming that the error terms in Equations (2) and (4), ε_{it}^c and υ_{it}^c, follow a bivariate Normal distribution:

$$\begin{pmatrix} \upsilon_{it}^c \\ \varepsilon_{it}^c \end{pmatrix} \sim N\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{pmatrix} \sigma_c^2 & \rho_c\sigma_c \\ \rho_c\sigma_c & 1 \end{pmatrix}\right). \tag{5}$$

The likelihood for household i in week t given latent state s can be written as (see Amemiya 1984, page 31):

$$l\left(Q_{it}^c \mid \beta^S, \phi^S\right) = \left(\frac{1}{\left(1-\rho_c/\sigma_c\right)^{\frac{1}{2}}}\Phi\left(\beta^S X_t^c + \frac{\rho_c\left(Q_{it}^c - \phi^S Z_t^c\right)}{\sigma_c}\right) * \ln\frac{1}{\sigma_c}\phi\left(\frac{Q_{it}^c - \phi^S Z_t^c}{\sigma_c}\right)\right)^{I_{it}^C} \left(\Phi\left(-\beta^S X_t^C\right)\right)^{(1-I_{it}^C)} \tag{6}$$

where $\phi(\cdot)$ is the probability density function and $\Phi(\cdot)$ is the cumulative distribution function of the Standard Normal distribution, respectively.

3.3.2 Hidden States and Transition Probabilities

Our main research question is whether and how purchase behavior, as measured by the baseline tendency and price sensitivity in purchase incidence and quantity decisions, evolves by the usage experience with various decision aids. To this end, 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}, which is 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 model 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 and Srinivasan 2008, page 190):

$$P_{it}(S_t = 1 \mid S_{t-1}, D_{it}) = \frac{\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1 + \exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},$$

$$P_{it}(S_t = 2 \mid S_{t-1}, D_{it}) = \frac{\exp(\lambda_{i2,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1 + \exp(\lambda_{i2,S_{t-1}} - \gamma_{s_{t-1}} D_{it})} - \frac{\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1 + \exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},$$

$$......$$ (7)

$$P_{it}(S_t = K \mid S_{t-1}, D_{it}) = 1 - \frac{\exp(\lambda_{iK-1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1 + \exp(\lambda_{iK-1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},$$

where K is the number of hidden states. Parameters $\lambda_{i1,s_{t-1}}, \lambda_{i2,s_{t-1}}, ..., \lambda_{iK-1,s_{t-1}}$ are household i's state-specific cut-off points and their values are set in ascending order for a given $S_{t-1} \in \{1, 2, .., K\}$. D_{it} is a vector of household i's usage experience with a set of decision aids, and $\gamma_{s_{t-1}}$ is a vector of their 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. 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 hidden state transition matrix. It captures individual differences in the behavior evolution, and automatically accommodates heterogeneity in parameter values in the consumer response model (i.e., the Tobit model).

The likelihood function for household i across different hidden states is (see Rabiner and Juang 1986; Rabiner 1989):

$$L(Q_i^C \mid \Theta_i^s) = P_i(Y_{i1} = Q_{i1}^c, Y_{i2} = Q_{i2}^c, ..., Y_{it} = Q_{iT}^c) = \sum_{s_1=1}^{K} \sum_{s_2=1}^{K} ... \sum_{s_T=1}^{K} [\pi_{is_1} \prod_{t=2}^{T} p_{i,s_t \mid s_{t-1}} \cdot \prod_{t=1}^{T} l(Q_{it}^c \mid \varphi^s, \beta^s)], \quad (8)$$

Where $\Theta_i^s = \{\phi^s, \beta^s, \lambda_{is,s_{t-1}}, \gamma_{s_{t-1}}\}$, and π_{is} is a vector of the initial state probabilities.

3.3.3 Prior Distributions and Estimation Method

The likelihood function in equation (8) is computationally intractable. Thus, we first re-write the likelihood function as the following (see Macdonald and Zucchini 1997, page 131)

$$NL_i(\Theta) = \pi_{s_{i,1}} \cdot f(X_1^C, Z_1^C, \Theta_i^{s_{i1}=s}) \cdot P_i(s_2 \mid s_1) f(X_2^C, Z_2^C, \Theta_i^{s_{i2}=s}) \cdot ... \cdot P_i(s_T \mid s_{T-1}) f(X_T^C, Z_T^C, \Theta_i^{s_{iT}=s}) \cdot 1', \quad (9)$$

where $f(X_t^C, Z_t^C \Theta_i^{s_{iT}=s})$ is an $K \times K$ diagonal matrix with likelihood $f_{s,s} = l(Q_{it}^c \mid \phi^s, \beta^s)$; $P_i(s_t \mid s_{t-1})$ is an $K \times K$ transition probability matrix from t-1 to t; $\mathbf{1'}$ is a column vector of ones with length K; π_{is_1} is the stationary distribution of transition matrix $P(s_t \mid s_{t-1})$, and is calculated according to equation (7) with covariates set to their mean values in the data.

Following the approach by Netzer et al. (2008), we divide the parameters into two sets: those that vary across individuals and those that do not. We use a hierarchical Bayes formulation to estimate the former group of parameters (e.g., Gelfand and Smith 1990; Rossi and Allenby 2003). The prior and hyper-prior are specified as follows:

(1) Parameters that vary across individuals:

$$\theta_i = \{\lambda_{is,s_{t-1}}\}; \theta_i \sim MVN(\delta, \Sigma_\theta)$$
$$\delta \sim MVN(\delta_0, V_0); \delta_0 \sim 0_{n\theta \times 1}; V_0 = 100 I_{n\theta}; \ n\theta = \dim(\theta_i)$$
$$\Sigma_\theta \sim IW(df_0, \Lambda_0); df_0 \sim n\theta + 5; \Lambda_0 = I_{n\theta} \quad (10)$$

(2): Parameters that do not vary across individuals:
$$\Psi = \{\beta^S, \varphi^S, \gamma_s\}; \Psi \sim N(\psi_0, V_{\psi_0})$$
$$\psi_0 \sim 0_{n\varphi \times 1}; V_{\psi_0} = 50 I_{n\varphi} \ (n\varphi = \dim(\Psi)) \quad (11)$$
$$P(\Psi) \propto \exp(\tfrac{1}{2}(\Psi - \psi_0)' V_{\psi_0}^{-1}(\Psi - \psi_0))$$

$\{\theta_i\}$ and $\{\Psi\}$ are drawn from Metropolis Hasting algorithm, while $\{\delta\}$ and $\{\Sigma_\theta\}$ are drawn from Gibbs sampler.

$$\{\theta_i\} \mid Q_{it}^C, X_t^C, Z_t^C, D_{it}, \delta, \Psi, \Sigma_\theta$$
$$\delta \mid \{\theta_i\}, M, \Sigma_\theta$$
$$\Sigma_\theta \mid \{\theta_i\}, M, \delta$$
$$\Psi \mid Q_{it}^C, X_t^C, Z_t^C, D_{it,,} \{\theta_i\} \tag{12}$$

We test our NHMM model on simulation data, where there are 40 households, each with 500 observations. The model recovered well on the simulation data (see Appendix III for the result).

3.4 Empirical Analyses

3.4.1 Data Description

Our data are provided by a leading Internet grocery retailer which was among the very first to sell groceries online. The dataset 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 our dataset particularly suited to study the evolution of purchase behavior in a new online environment.

The data include click-stream records of detailed navigation processes and purchase history information of 225 households, as well as pricing information for multiple product categories. We estimate the proposed model using data of two distinct product categories, spaghetti sauce and liquid detergent, in order to test the robustness of the results. These categories are chosen because they differ in terms of hedonicity and purchase frequency, which have been shown to affect consumers' in-store decision making processes (Inman, Winer, and Ferraro 2009). Only those households that made at least two category purchases during the 62-week data period are included in the data for a category.

3.4.2 Operationalization of Key Variables

As explained previously, we use price as the key marketing mix variable for the Tobit model of purchase incidence and quantity decisions in the empirical analysis. We first obtain the weekly actual price of each stock-keeping units (SKU) in a category by combining its regular price and price discount (if any), and then convert it to a common unit price (e.g., cents per ounce) across SKUs. The category-level price variable is computed as a weighted average of the weekly unit prices of all SKUs in the category, where the weights are sales volume shares of the SKUs in the entire time period.

Decision aid usage information is extracted from the click-stream data. We classify six types of decision aids that are commonly available in most online stores and fall into one of the four broad categories described earlier, including one for nutritional needs, one for brand preference, two for economic needs, and two for personalized shopping lists (see Table 3.1). 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 avoids possible reverse causality, that is, purchase behavior may influence the current usage of decision aids. Note that a household can use the same decision aid multiple times during a single shopping session and the cumulative experience variables count for each and every time a given decision aid is used by a household. A main objective of our research is to investigate how usage experience with different decision aids may drive purchase behavior changes over time. To this end, the transition probability functions of the proposed Hidden Markov Model include the usage experience variables of multiple decision aids. Since the usage experience with each decision aid increases monotonically with time, a more meaningful measure for the model is the relative usage experience with each decision aid, computed as a percentage of the household's total

number of usage counts of all decision aids up to week *t-1*. We also include the total decision aid usage variable to account for its potential effect on the transition probabilities.

Descriptive statistics of the key variables for each product category are presented in Table 3.2. Note that the usage experience variables are store-level measures and thus do not vary across categories. For each decision aid examined, we report its cumulative usage counts and as a percentage of the total usage counts, for up to week *t-1* as well as by the last week in the data (Week 62). As the table shows, shopping list is the most frequently used decision aid (30.66 times on average in 62 weeks), far out-numbering the usage of the other types of decision aids, followed by previous order list (5.27 times), sorting by brand name (4.06 times), sorting by nutrition (1.93 times), sorting by price (1.17 times) and sorting by promotion (.38 times). As shown by the standard deviations, the experience measures vary substantially across individuals. Since we need to exclude at least one of the relative usage experience variables from the model to avoid perfect collinearity, we choose to take out sorting by promotion because it had the lowest occurrence amongst the six focal decision aids of interest.

[INSERT TABLES 3.1 & 3.2 HERE]

3.4.3 Time-Varying Patterns of Usage Experience with Decision Aids

To inspect how the usage experience 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 3.1). Note that the relative usage experience measures do not necessarily sum up to 100% in all weeks because some households had not tried any decision aids in the earlier weeks. The relative usage experience with personal shopping list and previous order list, which implies habitual decision processes, increases over time; while the relative usage experience with sorting by brand name, by price, and by promotion, which are indicative of on-the-spot decision

processes, levels off in the later stage of the observation period. This is consistent with previous literature which suggests that weights of price information will decrease when other product attributes are available (Anderson 1971and 1981; Bettman, Capon, and Lutz 1975). The time-varying patterns of the different decision aids indicate that, on average, consumers tend to adopt more habitual behavior and make fewer on-the-spot purchase decisions as they get more accustomed to the type of online shopping environment as studied here.

[INSERT FIGURE 3.1 ABOUT HERE]

3.4.4 Model Estimation Results

In Table 3.3, we compare the BIC, DIC, and log-marginal densities of models with different numbers of hidden states to determine the best number of states for each category (see Hughes, Guttorp, and Charles 1999; Netzer et al. 2008). These comparisons indicate that a three-state model fits the data best for both spaghetti sauce and liquid detergent. Estimation results of the three-state model for the two categories are presented in Tables 3.4 and 3.5, respectively.

[INSERT TABLES 3.3, 3.4, and 3.5 ABOUT HERE]

As shown by Table 3.4, households' purchase behavior differ substantially across the three hidden states for the spaghetti sauce category. By the model construction, the baseline purchase incidence tendency increases from hidden state 1 (S1) to hidden state 3 (S3). Our empirical result shows that the same order of baselines also holds for purchase quantity decisions across the three states, even though they are not constrained to be so. Price has a negative and "significant" effect on the purchase incidence probability in all three states[5], but its effect is the strongest in S2 (-.620), followed by S1 (-.144), while its effect in S3 is much smaller (-.005). The

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[5] For the ease of exposition, hereafter, we report the posterior means in parentheses and use the term "significant" to refer to the case where the posterior 95% credible interval does not cover zero.

same pattern of price sensitivity also holds for the purchase quantity decision. Thus, S1 represents a low baseline purchase tendency (i.e., store loyalty) and medium price sensitivity state, S2 is characterized as having medium baseline purchase tendency and the highest price sensitivity decisions, and S3 exhibits the highest baseline purchase tendency and the lowest price sensitivity.

The three hidden states of the liquid detergent category show very similar patterns, and can be interpreted in the same fashion.

The lower panels of Table 3.4 and Table 3.5 report parameter estimates of the variables that affect the transition probabilities between hidden states. For the spaghetti sauce category, when consumers are in S1, more usage experience with sorting by brand name significantly increases the probability of staying in S1 and reduces the probability of switching to the more store-loyal states S2 and S3 (posterior mean = -2.578), while the total decision aid usage significantly increases the probability of switching to a more store-loyal state (posterior mean = 1.153). When consumers are in S2, more usage experiences with sorting by brand name and sorting by price discourage the transition to S3 while encourages the transition to S1 (posterior mean = -1.071 and -.420, respectively), while more usage experiences with sorting by nutrition and personal shopping lists have the opposite effects (posterior mean = .410, and 1.950, respectively). When consumers are in S3, more usage experiences with personal shopping lists and previous order lists increase the likelihood of staying in S3 and reduce the transition probabilities from S3 to a less store-loyal state (posterior mean = .946 and .495, respectively).

The effects of the usage experience variables exhibit a similar pattern in the liquid detergent category. When consumers are in the least store-loyal state (S1), more usage experience with sorting by brand name discourages switching to the states with higher levels of

store loyalty (S2 and S3). It is possible that consumers with strong brand preference (brand loyalty) are willing to switch stores if the preferred brand is not available in the focal store. When consumers are in the medium store-loyalty state (S2), usage experiences of sorting by brand name and sorting by price increase the probability of switching to S1 and reduce the probability of switching to the most store-loyal state (S3), while usage experiences with personal shopping lists and previous order lists, as well as the total decision aid usage count, have the opposite effects. When consumers are in the most store-loyal state (S3), usage experiences of personal shopping lists and previous order lists and the total decision aid usage count reinforce the probability of staying in this state and decrease the chance of switching to a less store-loyal state, while usage experiences with sorting by brand name and by price do not have any significant effects any more.

An interesting contrast with results of the spaghetti sauce category is that, for the liquid detergent category, usage experience with sorting by nutrition does not have any effects on the purchase behavior evolution. This difference between the two categories is expected, and it attests to our model's ability detect the distinct effects (or the lack of which) of usage experience with different decision aids.

3.4.5 Evolution of Purchase Behavior in the Online Store

Our results indicate that there are different hidden behavior states and consumers switch among these states over time, reflecting an evolution of purchase behavior when shopping in a new online store environment. To investigate the time varying patterns of the purchase behavior, we need to compute the posterior distribution of the three states for each household in each week, and then explore the relationship between price sensitivity measures and the usage experience variables.

3.4.5.1 State Probability Distribution

To better understand the evolution of purchase behavior, we firstly examine the probabilities of the states for each household over time. The filtering probability of household *i* belonging to state *s* at week *t* (Netzer, et al. 2008) can be calculated as:

$$\mathrm{Pr}ob(S_{i,t} = s \mid I_{i1}, I_{i2}, ... I_{it}, Q_{i1}, Q_{i2}, ..., Q_{it})$$
$$= \pi_{s_{i1}} \cdot f(X_1^C, Z_1^C, \Theta_i^{s_{i1}=s}) \cdot P_i(s_2 \mid s_1, s) f(X_2^C, Z_2^C, \Theta_i^{s_{i2}=s}) \cdot ... \cdot P_i(s_t \mid s_{t-1}, s) f(X_t^C, Z_t^C, \Theta_i^{s_{it}=s}) / l(Q_{it}^c \mid \phi^s, \beta^s), (13)$$

where $\boldsymbol{P_i}(s_t/s_{t-1},s)$ is the sth column of transition matrix $\boldsymbol{P}(s_t/s_{t-1})$, $l(Q_{it}^c \mid \phi^s, \beta^s)$ is the likelihood of the observed purchase incidence and quantity up to week *t*. Figure 3.2 presents the average probabilities of belonging each state in 62 weeks. For the spaghetti sauce category, the average probability of belonging to S1, which has the lowest store loyalty and medium price sensitivity, decreases substantially over time (from 67.86% in week 1 to 16.01% in week 62). In contrast, the average probabilities of belonging to S2 and S3 increase over time (S2: from 19.03% in week 1 to 30.48% in week 62; S3: from 13.11% in week 1 to 53.50% in week 62). On average, consumers are more likely to be in S1 than in the other two states in the first half of the observed period (till week 32). The average probability of belonging to S3, the state with the highest store loyalty and lowest price sensitivity, surpasses that for S2, and S3 becomes the dominant behavior state from week 32 and on. This pattern also holds for the liquid detergent category: the average probability of belonging to S1 declines while those for S2 and S3 increase over time, and S3 becomes the dominant behavior state since week 39, for the average consumer.

[INSERT FIGURE 3.2 ABOUT HERE]

3.4.5.2 Effects of Usage Experience with Decision Aids on Price Sensitivity

Since the states are not in ascending or descending order, the direction of the changes of price sensitivity, and the relationship between the usage experience with decision aids and the

price sensitivity are unknown based on the model estimation per se. Therefore, we compute a posterior price sensitivity measure for each household in each week, and then regress this measure on the usage experience variables. To account for uncertainty in posterior distributions of price coefficients, we calculate a weighted posterior price sensitivity measure.

Specifically, we take the last 1,000 draws of the price coefficients, and for each draw, price coefficients for household i in week t are weighted by its probabilities of belonging to each corresponding hidden state in that week. Then we average the weighted price coefficients across the 1000 draws to get the price sensitivity measure for each household across 62 weeks. The time-varying patterns of price sensitivity measures are plotted in Figure 3.3 and 3.4, for the spaghetti sauce and liquid detergent categories, respectively.

For the spaghetti sauce category, the average values of the price sensitivity measures for purchase incidence and purchase quantity firstly increase then decrease over the observed period (see the upper panels in Figure 3.3). In addition, the variances of these measures increase over time, indicating that consumers' price sensitivity diverges over time, with some becoming less price-sensitive while other becoming more price-sensitive, as they become more accustomed to an online store environment (see the lower panels in Figure 3.3). The plots for the liquid detergent category reveal the same patterns. Prior research shows that a higher degree of heterogeneity in price sensitivity is conducive to more granular price promotion customization (Zhang and Wedel 2009). This divergence in price sensitivity over time suggests that online retailers have a good opportunity to customize their price promotions to cater to individual consumers' needs and preferences, as consumers become more used to shopping online. In the following, we will examine the impact of different decision aids on price sensitivity through post-hoc analysis.

[INSERT FIGURE 3.3 and 3.4 ABOUT HERE]

Since the hidden states identified by our model are not ordered by their level of price sensitivity, we cannot directly infer from the parameter estimates how usage experience with each decision aids affects consumers' price sensitivity evolution. To investigate this issue, we conduct regression analyses where the dependent variables are the price sensitivity measures for the purchase incidence or the purchase quantity decision, and the explanatory variables are the usage experience with different decision aids. We use a random-effect model to allow heterogeneity in price sensitivity across households. The price coefficients are estimated from the models, and thus the dependent variables are also measured with uncertainty. Since the posterior distributions of the price coefficients are unknown, we use the simulated maximum likelihood estimation (MLE) method to estimate the models, where the draws of the price coefficients are a natural product of the MCMC procedures of the main model estimation. We use the last 1,000 draws of each MCMC procedure for the simulated MLE.

Table 3.6 present the results of these regression analyses. For both categories, usage experience with personal shopping lists and previous order lists can mitigate consumers' price sensitivity in purchase incidence decisions, and make them more loyal to the focal retailer. In contrast, usage experience with sorting by price can train consumers to become more efficient at using price information in the liquid detergent category and thus more sensitive to it in their purchase decisions. Usage experience with sorting by brand name also leads to higher price sensitivity in the spaghetti sauce category. Thus, the more usage experience with such decision aids, the more responsive consumers become to price changes.

[INSERT TABLE 3.6 ABOUT HERE]

67

3.5 Discussion

In this study, we investigate whether and how the usage experience with different decision aids drives the evolution of purchase behavior. We empirically identified three latent states that direct the purchase behavior over time. They are: hidden state 1where consumers show lowest store loyalty /medium price sensitivity; hidden state 2 that characterized with medium store loyalty /high price sensitivity; and hidden 3 that exhibits highest store loyalty /low price sensitivity. Post-hoc analysis shows that the probabilities of staying in hidden state 1 declines over time, while the probabilities of staying in the other two hidden states demonstrate a reverse trend. In the latter half of the 62-week period, hidden state 3 dominates. Such pattern implies that as consumers get more accustomed to the online store environment, their baseline tendency to purchase from the store increases. In addition, their price sensitivity diverges over time, with some consumers becoming more price sensitive, while others becoming less price sensitive.

The transitions among these hidden states are driven by the relative usage experience with different decision aids. For both spaghetti sauce and liquid detergent categories, more relative usage experience with the decision aids for brand preference (sorting by brand names) discourages the transitions from lower store-loyal state to higher store-loyal state. More relative usage experience with decision aids for economic needs (sorting by price) also reduces the transition probabilities from lower store-loyal state to higher store-loyal state, in addition, post-hoc analyses show that usage experience with sorting by price in the liquid detergent category trains consumers to become more responsive to price changes. In contrast, more relative usage experience with decision aids for personalized shopping list, such as shopping list and previous order list, as well as sorting by nutritional information for the spaghetti sauce category, increase

the transition from medium store-loyal / high price sensitive state (hidden state 2) to high store-loyal / low price sensitive state (hidden state 3). Post-hoc analysis also confirmed the inverse relationship between the usage experience with personalized shopping lists and price sensitivity. Personalized shopping lists thus help build store loyalty, increase purchase propensity, and ease price competition.

These findings have important implications for the design of online store environments and communication messages regarding a firm's pricing decisions. To encourage transition from the more price sensitive state to less price sensitive, online retailers should allow consumers to create shopping lists, make available their previous order lists, provide decision aids for searching a variety of nutritional information, and encourage their usage among the customers. The personalized shopping lists will create a lock-in effect and help consumer build store loyalty. Decision aids aimed at economic needs, on the other hand, are a double-edged sword. A low-price online retailer could benefit from higher consumer responsiveness to price by enabling and promoting the usage of such type of decision aids like sorting by price, but usage of these decision aids would lower consumers' loyalty to the store in the long run. In addition, their usage could negatively affect the long-term business for retailers that adopt a premier pricing strategy and do not compete on promotions. What decision aids to offer and to emphasize should depend on an online retailer's overall positioning and pricing strategies, and weigh in the trade-offs of the retailer's short-term versus long-term needs.

In terms of future research, it would be interesting to investigate whether there are carry-over effects of usage experience across product categories, i.e., would the usage experience in one product category affect the evolution of purchase behavior in other categories. Effects of the store-level usage experience variables, as shown by our study, strongly suggest such possibility.

69

Given the proliferation of multi-channel retailing, another worthy direction is to study the impact of usage experience with online decision aids on offline purchase behavior offline, which would require matching online navigation data and offline purchase history data. In addition, how the pattern of decision aids usage evolves over time itself is an interesting topic to explore. All these topics offer exciting venues for gaining deeper understanding of purchase behavior evolution in the ever-evolving retail environment.

Table 3.1 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 list	Shopping List	Retrieve and use personal shopping list
	Previous Order List	Retrieve and use previous order list

Table 3.2 Descriptive Statistics

Variable (mean/sd of variables across weeks and across individuals)	Cumulative usage count up to week t-1		As percentage of total decision aid usage up to week t-1 (%)	
	Mean	**S.D.**	**Mean**	**S.D.**
Store Level Tool Usage:				
--- Sort by Nutrition	1.06	4.23	3.96	9.85
--- Sort by Brand Name	2.32	6.36	7.99	16.60
--- Sort by Price	0.75	2.25	2.91	8.81
--- Sort by Promotion	0.25	0.73	1.42	5.65
--- Shopping List	16.70	30.3	55.71	37.35
--- Previous Order List	2.71	5.75	12.42	21.73
--- Total decision aid usage (six tools)	23.79	38.04		

Variable (mean/sd of last week's measure for all individuals)	Cumulative usage count in week 62		As percentage of total decision aid usage in week 62 (%)	
	Mean	**S.D.**	**Mean**	**S.D.**
Store Level Tool Usage:				
--- Sort by Nutrition	1.93	6.30	4.55	9.19
--- Sort by Brand Name	4.06	8.52	10.29	17.74
--- Sort by Price	1.17	3.03	3.43	10.83
--- Sort by Promotion	0.38	0.91	1.50	5.34
--- Shopping List	30.66	47.18	63.67	31.36
--- Previous Order List	5.27	8.92	16.56	23.67
--- Total decision aid usage (six tools)	43.47	57.17		

Variable	Mean	S.D.	
Category 1: Spaghetti Sauce (N = 137 households)			
Purchase frequency (times/per year)	5.63	6.15	
Purchase quantity (ounces/occasion)	34.62	21.23	
Regular price (cents/oz.)	9.03	0.37	
Price discount (cents/oz.)	0.31	0.25	
Paid price (cents/oz.)	8.64	0.42	
Category 2: Liquid Detergent (N = 159 households)			
Purchase frequency (times/per year)	5.53	6.49	
Purchase quantity (ounces/occasion)	124.70	69.25	
Regular price (cents/oz.)	7.15	0.30	
Price discount (cents/oz.)	0.48	0.38	
Paid price (cents/oz.)	6.67	0.45	

Table 3.3 Model Comparisons

Number of Hidden States	Spaghetti Sauce			Liquid detergent		
	LMD	BIC	DIC	LMD	BIC	DIC
K=2	-4,786.7	9,565.0	9,430.9	-5,992.6	12,078.9	11,901.2
K=3	-4,128.4	8,426.9	8,217.3	-5,337.1	10,848.2	10,692.1
K=4	-4,593.1	9,583.3	9,492.5	-5,889.3	12,184.5	12,103.2

Note: LMD = log-marginal density;
BIC = Bayesian Information Criterion;
DIC = Deviance Information Criterion.

Table 3.4 Estimation Result for Spaghetti Sauce

Variables in the Tobit Model	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%
Purchase Incidence									
Intercept	**-2.171**	-3.055	-1.287	-1.787	-2.148	4.170	**-1.080**	-1.255	-0.847
Actual price	**-0.144**	-0.149	-0.140	**-0.620**	-1.204	-0.036	**-0.005**	-0.007	-0.003
Purchase Quantity									
Intercept	**0.960**	0.302	1.618	**2.190**	2.081	2.310	**2.258**	2.193	3.907
Actual price	-0.279	-0.605	0.046	**-0.926**	-1.718	-0.135	0.001	-0.019	0.021

Variables Affecting the Transition Probabilities (relative usage experience)	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%
Cut-off point 1	1.248	-0.014	2.509	**2.067**	1.231	2.904	**0.939**	0.545	1.133
Cut-off point 2	**1.314**	1.183	1.444	2.648	-0.875	6.171	**1.937**	0.301	3.572
Sort by Brand Name	**-2.578**	-4.024	-1.131	**-1.071**	-1.459	-0.683	-0.621	-1.536	0.293
Sort by Price	-0.236	-1.070	0.597	**-0.420**	-0.597	-0.243	-0.008	-0.269	0.253
Sort by Nutrition	-0.838	-1.846	0.171	**0.410**	0.019	0.802	-0.585	-2.331	1.162
Shopping List	1.182	-0.051	2.414	**1.950**	0.928	2.972	**0.946**	0.351	1.540
Previous Order List	-0.460	-1.273	0.353	0.685	-0.019	1.390	**0.495**	0.230	0.760
Total decision aid usage	**1.153**	0.647	1.658	2.013	-0.008	4.035	0.489	-0.713	1.691

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

Table 3.5 Estimation Result for Liquid Detergent

Variables in the Tobit Model	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%
Purchase Incidence									
Intercept	**-0.707**	-1.195	-0.219	**1.228**	0.102	1.027	**1.384**	0.637	2.130
Actual price	-0.228	-2.341	1.886	**-0.496**	0.121	-0.733	**-0.100**	-0.116	-0.084
Purchase Quantity									
Intercept	**-1.374**	-1.645	-1.103	3.102	-1.164	5.368	**3.925**	3.052	4.798
Actual price	-0.859	-2.057	0.340	**-1.441**	-1.571	-1.311	**-0.120**	-0.239	-0.001

Variables Affecting the Transition Probabilities (relative usage experience)	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%	Posterior mean	2.50%	97.50%
Cut-off point 1	**-1.310**	-2.380	-0.241	-0.235	-0.812	0.342	**-1.073**	-1.851	-0.296
Cut-off point 2	**-0.953**	-1.027	-0.878	**0.701**	0.279	1.123	**1.102**	0.537	1.667
Sort by Brand Name	**-0.380**	-0.532	-0.229	**-0.104**	-0.149	-0.059	-0.053	-1.711	1.604
Sort by Price	-0.804	-1.616	0.009	**-1.023**	-1.627	-0.420	0.157	-1.250	1.563
Sort by Nutrition	-0.016	-0.578	0.546	0.134	-1.603	1.870	0.035	-1.440	1.510
Shopping List	0.142	-0.115	0.398	**1.149**	0.743	1.556	**1.928**	0.792	3.065
Previous Order List	0.767	-1.003	2.537	**0.987**	0.606	1.367	**0.586**	0.118	1.054
Total decision aid usage	1.466	-0.228	3.160	**1.259**	0.247	2.270	**1.276**	0.924	1.628

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

Table 3.6 The Impact of Usage Experience with Decision Aids on Price Sensitivity (Simulated MLE)
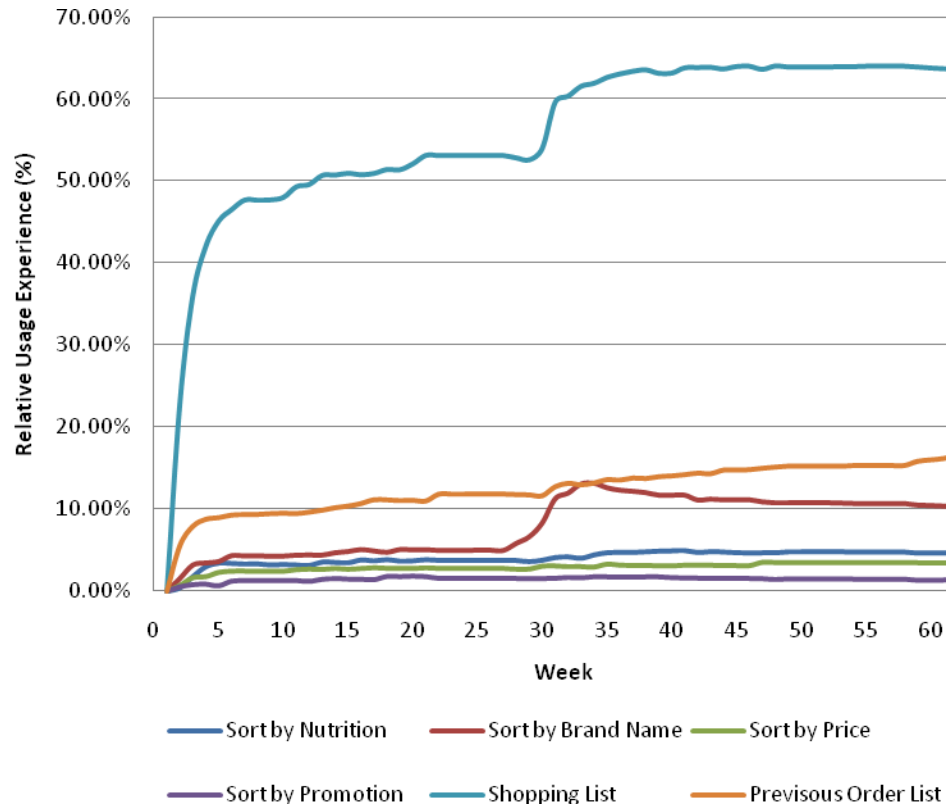
Spaghetti Sauce

	Purchase Incidence				Purchase Quantity			
	Mean	**S.E.**	**t-stat**	***P*-value**	**Mean**	**S.E.**	**t-stat**	***P*-value**
Intercept	0.113	0.006	17.523	0.000	0.228	0.008	29.497	0.000
Intercept_var	0.215	2.508	-0.612	0.542	0.361	1.730	-0.589	0.557
Sort by Brand Name	-0.022	0.011	-2.066	0.041	-0.005	0.018	-0.301	0.764
Sort by Price	-0.015	0.033	-0.463	0.644	-0.011	0.051	-0.213	0.832
Sort by Nutrition	0.019	0.029	0.677	0.499	0.025	0.034	0.739	0.461
Shopping List	0.032	0.008	4.112	0.000	0.027	0.015	1.781	0.077
Previous Order List	0.022	0.011	1.998	0.048	-0.002	0.009	-0.268	0.789

Liquid Detergent

	Purchase Incidence				Purchase Quantity			
	Mean	**S.E.**	**t-stat**	***P*-value**	**Mean**	**S.E.**	**t-stat**	***P*-value**
Intercept	0.214	0.004	58.584	0.000	0.683	0.053	12.980	0.000
Intercept_var	0.218	0.424	3.586	0.000	0.204	0.213	7.443	0.000
Sort by Brand Name	-0.002	0.010	-0.209	0.835	-0.008	0.019	-0.417	0.677
Sort by Price	-0.135	0.068	1.981	0.049	-0.032	0.022	-1.456	0.147
Sort by Nutrition	0.013	0.015	0.873	0.384	0.003	0.003	1.050	0.295
Shopping List	0.058	0.014	4.056	0.000	0.787	0.037	21.327	0.000
Previous Order List	0.032	0.012	2.739	0.007	0.059	0.010	5.727	0.000

Figure 3.1

Time-Varying Patterns of Usage Experience with Decision Aids

Figure 3.2 Probabilities of Belonging to Each State

Spaghetti Sauce
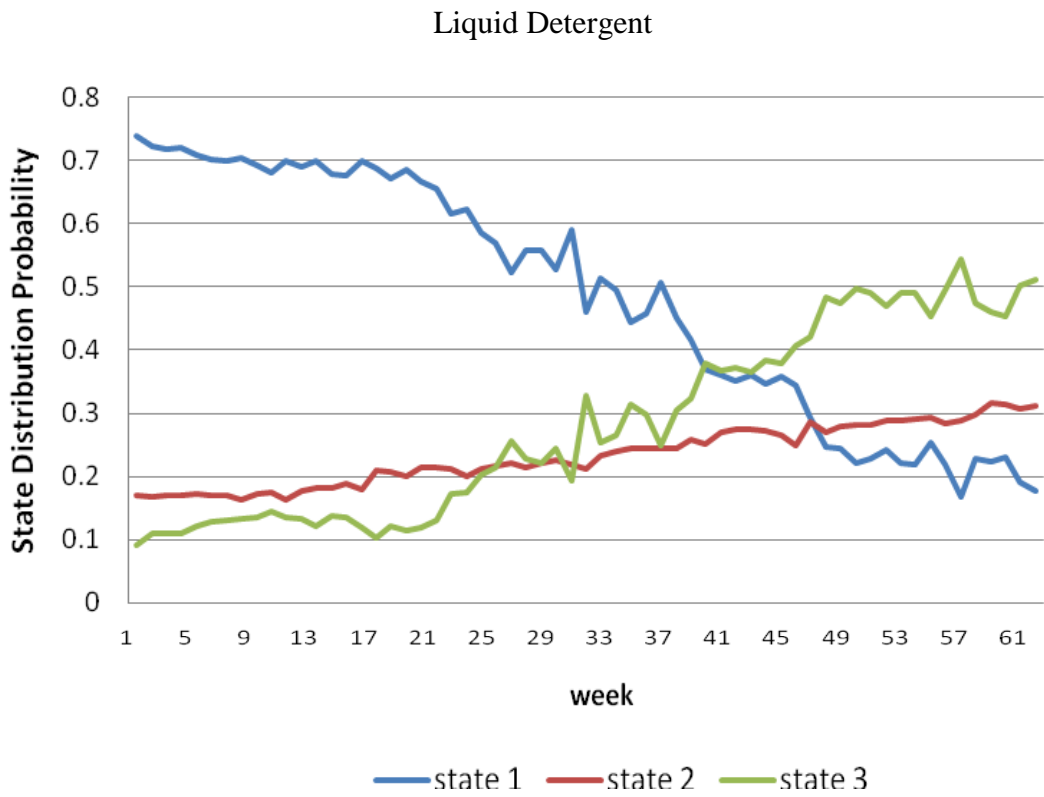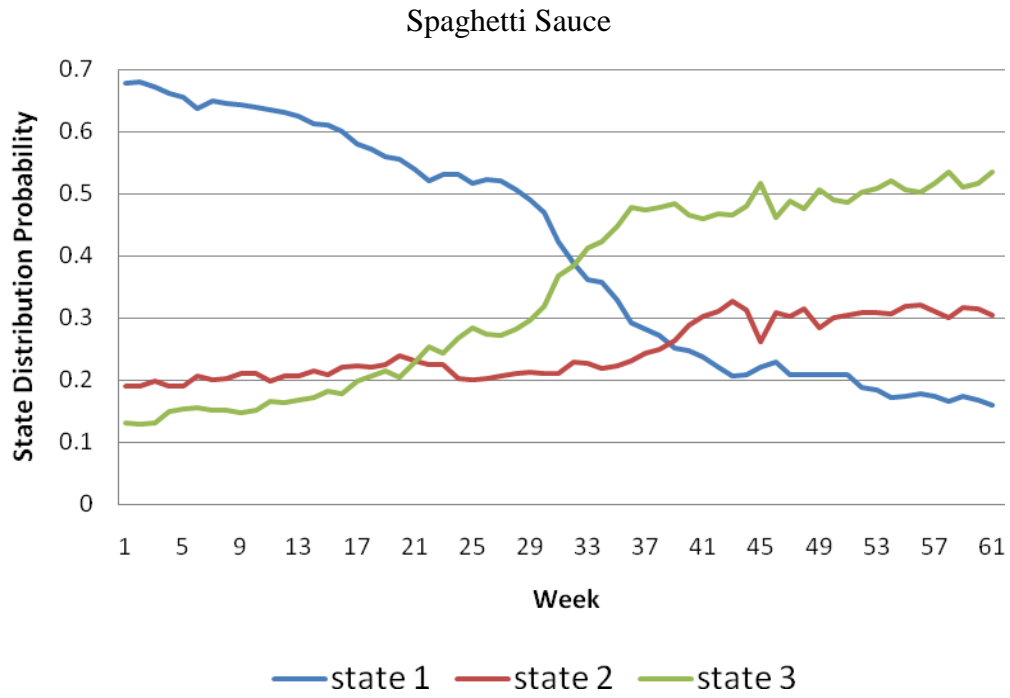
Liquid Detergent

Figure 3.3 Evolution of Price Sensitivity over Time

Spaghetti Sauce

Liquid detergent
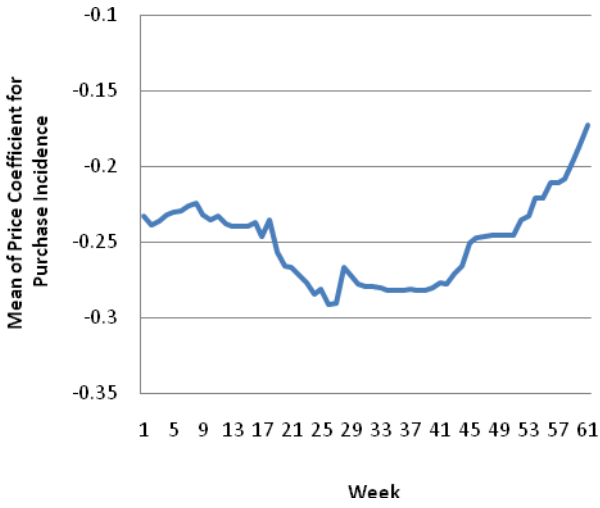
Chapter IV: Conclusion

This dissertation empirically investigates dynamic consumer decision processes in E-Commerce settings. In this chapter, we will re-examine the findings from Chapter 2 and 3, points out the contributions of this dissertation, and conclude with an exploration of possible future directions for this stream of research.

4.1 Summary of the Two Essays

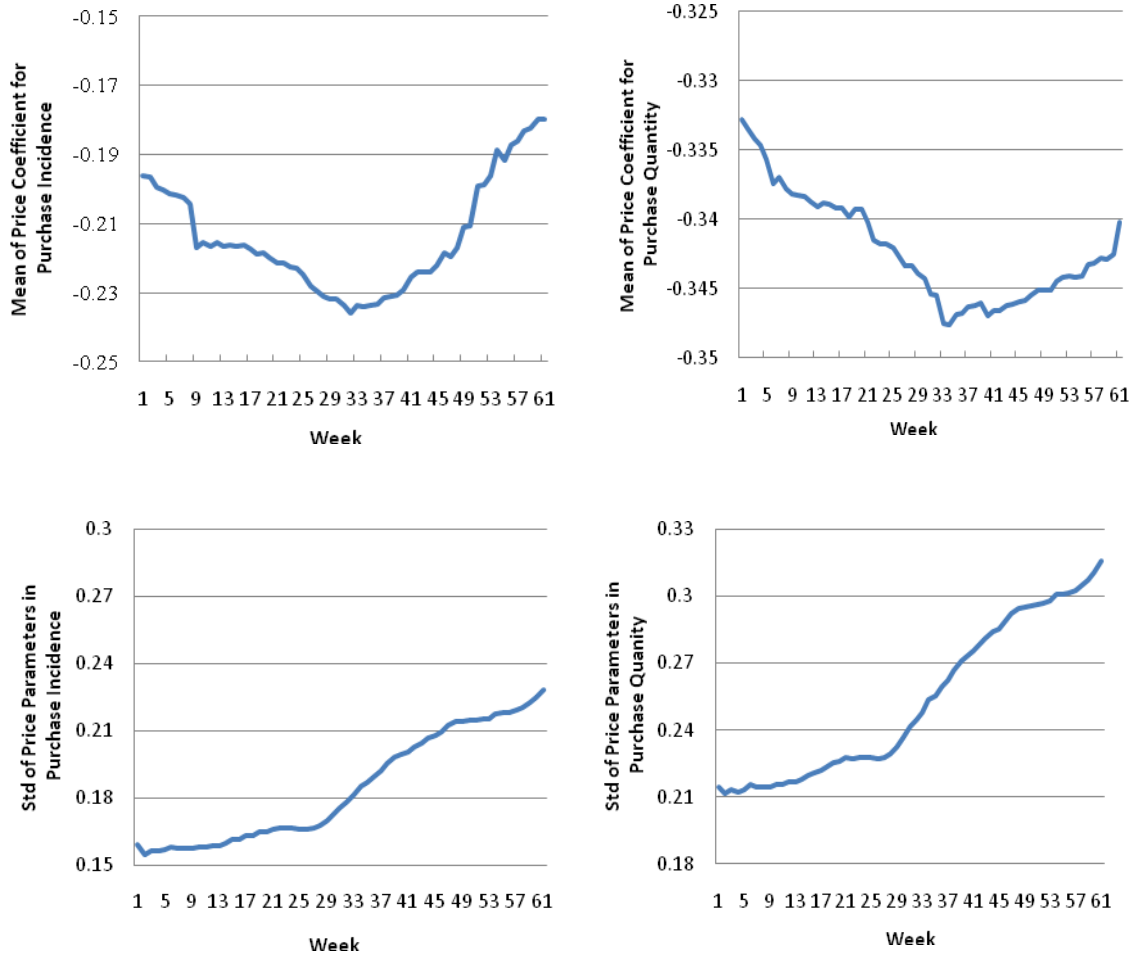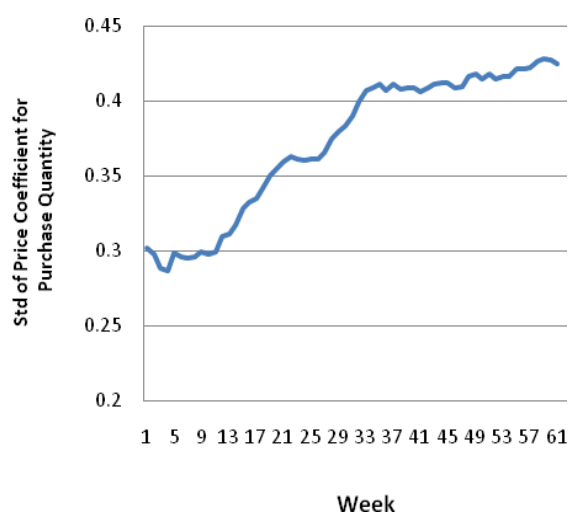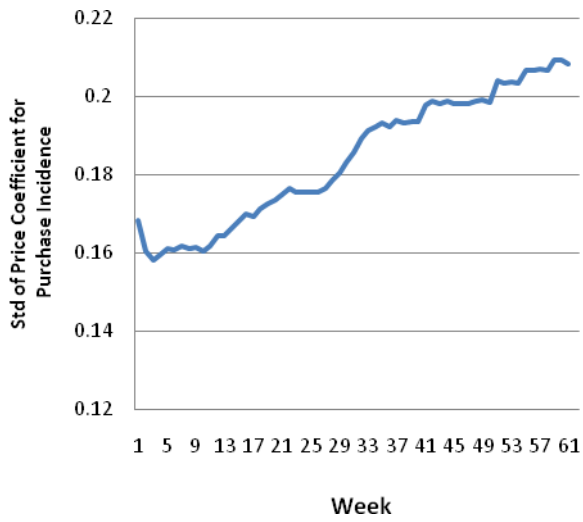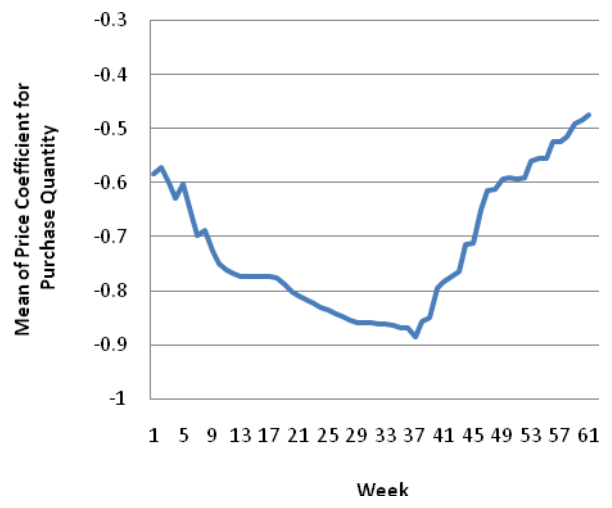Essay one uses eye tracking data to investigate information acquisition processes on attribute-by-product matrices as encountered in online comparison websites. The study identifies two information acquisition modes (attribute-based or product-based), and documents the extent of usage and switching of these acquisition modes through Hierarchical Hidden Markov Model (HHMM). Post-hoc analyses focus on the specific information processed in these modes, the possible causes and consequences of switching, and the dynamics in the comparison set during decision making. We find that the low-level properties of the eye and the visual brain (horizontal and local eye movement tendency) stimulate congruent information processing mode and contiguous information acquisition, reflecting a stronger influence on information acquisition processes than previously documented in the traditional process-tracing studies. In addition, we find frequent switching between acquisition modes when consumers face information-rich comparison websites. The extensive switching might be explained from the previously obtained information, and limited visual short term memory. Higher switching frequency significantly increases decision time, and reduces the experienced ease-of-processing.

Essay two conducts an empirical investigation on whether and how usage experience with various types of decision aids affects the evolution of online purchase behavior. By

adopting Non-homogeneous Hidden Markov Model (NHMM), we empirically identified three

latent behavior states that govern the evolution of online purchase behavior and the drivers

behind the evolvement of behavior. As consumers get more accustomed to the online store

environment, their baseline tendency to purchase from the store increases, and their price

sensitivity diverges over time. More relative usage experience with shopping lists, previous order

list, and sorting by nutrition (in Spaghetti sauce category), encourages the transition from

medium store-loyal/high price sensitivity state to high store-loyal /low price sensitivity state; yet

more relative usage experience with sorting by brand name and sorting by price reduces the

probability of switching from lower store-loyal state to higher store-loyal state. Post-hoc analysis

reveals that more usage experience with sorting by brand name in the spaghetti sauce category

and sorting by price in the liquid detergent category increase price sensitivity, while personalized

shopping lists are important decision aids that help retailers build store loyalty and soften the

price competition.

4.2 Contribution and Managerial Implications

This dissertation has made the following contributions:

Firstly, we take advantage of recent development in technology and investigate the

dynamic decision making process with eye tracking data and online navigation data. These path

data opens up the possibilities to exploit micro-level dynamics during decision making. In the

first study, we rely on eye tracking equipment to accurately document moment to moment

information search activities when consumers making their purchase on comparison websites.

The eye tracking equipment is able to capture fast, adaptive, partially unconscious information

acquisition behavior during real-life decision making. This is different from traditional process

tracing methods such as information display boards. Prior process tracing methods require motor

responses, which renders the information acquisition process more controlled and deliberate. As a consequence, these studies could discover mostly high-level and slower cognitive processes that consumers engage in during decision making. Thanks to the eye movement data, our study is able to offer a sneak peek into both "overt and covert", and "voluntary and involuntary" aspects of decision process (Lynch and Srull 1982). Low-level properties of the eye and the visual brain that are underexploited in previous accounts of decision process, appear to play an important role when decision-making is fast and more automatic. Insight into these covert and involuntary information tendencies will lead to a better understanding of decision-making in information-rich online choice environments.

In the second study, we collect online navigation data and purchase history data to investigate purchase behavior evolution. What is lacking in the literature is a comprehensive, longitudinal examination of the evolving patterns of purchase behavior, and more importantly, the drivers behind purchase behavior changes in online stores. Our study fills this void by extracting the information of decision aids usage from online navigation data and using it to explain the evolution of purchase behavior. Navigation data provides valuable information of consumers' online activities. The usage experience with decision aids extracted from navigation data reveals the information search and evaluation process before purchase occurs. It impacts the weights of different attributes including price, the extent of brand and store loyalty, the importance of personalized shopping environment, etc. The usage experience data collected over time reflects learning and adaptation processes that consumers go through when shop in a new channel. This information is helpful in explaining the evolution of purchase propensity and responsiveness to marketing mix, yet difficult to obtain in offline settings.

Secondly, we adopt a flexible evolutionary structure to model decision dynamics. Eye movement data is dense, stochastic, and highly dynamic. It reflects the latent information acquisition modes probabilistically, rather than deterministically. The HHMM in essay one deals with large volumes of eye movement data, unobserved information modes, and a probabilistic link between these two through structural restrictions. The model effectively copes with the challenge to extract diagnostic information from the massive amount of eye movement data. The three hierarchical layers in HHMM represent longer range dependencies in eye-movements, and quantitatively capture prevalence and flexible switching pattern of information acquisition modes.

The classification of different purchase behaviors has been a long-standing research interest in the marketing literature. In essay two, we propose that the observed online shopping behavior is likely to be directed by certain latent "behavior states", and these hidden states differ in terms of the baseline tendency to purchase from the online store and their price sensitivity. NHMM automatically identifies three latent behavior states, and allows flexible transitions among these behavior states. In addition, the non-homogeneous structure in NHMM enables us to explore the drivers behind the evolutions of these hidden states, and reveals how the store environment trains consumers and changes their behavior states over time.

Managerially, our results have implications for the design of online shopping websites which are gaining popularity recently. Retailers and manufacturers try to optimize online information displays to affect consumers' information acquisition processes and their purchase decision. The first study shows that low-level, automatic and unconscious processes are principal in situations of information overload and time pressure, which occur when facing data-rich web-based choice environments. Comparison website developers could display formats in a proactive

fashion to stimulate consumers' use of specific information acquisition mode favorable to their goals. Dominance of local information acquisition requires careful allocation of attributes / products. By strategically placing the contiguous information, retailers may be able to alternate the attractiveness of certain attribute. A delicate balance among format, sales objective, and switching cost is also needed. For example, we find that that a Product-Column format invites more attributed-based acquisition and increases the chance of the dominant product being chosen; while a Product-Row format leads to more evenly distributed choice probabilities. However, the latter format leads to more local eye movements and switching between acquisition modes, smaller numbers of products and attributes being inspected, and reduced ease of decision making. In addition, some comparison websites that enable sorting by certain attribute may need to reconsider their default format, which is the Product-Row format. This format may be in conflict with desirable attribute-based information processing for these websites.

The second study reveals that the more usage experience with personalized shopping list, and sorting by nutrition (in the spaghetti sauce category) leads to the transition from medium store-loyal/high price sensitivity behavior state to high store-loyal/low price sensitivity behavior state; while more usage experience with decision aids for economic needs and brand preference discourages the transition from lower store-loyal states to higher store-loyal states. If online retailers could encourage consumers to create and store personal shopping lists, make available their previous order lists, and encourage their usage among the customers, it will facilitate the transition from the more price sensitive state to the less price sensitive state, create a lock-in effect, build store loyalty, and train consumers into habitual shoppers. Retailers should be careful with the offering of decision aids aimed at economic needs, however. A low-price-driven online retailer could benefit from higher consumer responsiveness to price by enabling and

85

promoting the usage of such type of decision aids, yet the long-term business may be harmed. Our study also provides some insights for online retailers to offer personalized shopping environment. Information of previous usage of decision aids and purchase behavior collected in the navigation data enables retailers to infer the distribution of different latent behavior states for individual customers. Retailers could customize the marketing mix variables based on the purchase propensity and price sensitivity of each behavior states; and encourage the usages of certain decision aids to influence customer's purchase evolution path.

4.3 Future Research

We hope this dissertation will stimulate further research interest in the dynamic decision making process in the online shopping environment. The first study raises several intriguing questions, for instance, how to effectively reduce frequent switching between different information acquisition modes? How do other design factors, such as sorting, grouping, trimming, and highlighting, affect the dynamic information acquisition processes and post-decision evaluations? Based on information acquisition patterns, can comparisons websites automatically adapt display format during decision making and increase the conversion rate?

The second study also offer several exciting research opportunities, for instance, what drives the evolution of decision aids usage itself over time? How does the usage experience with decision aids online affect the purchase behavior offline? Will the usage experience with one product category affect the evolution of purchase behavior in the other category ("spill-over" effect)? All these future research questions will help us enrich our understandings of dynamic decision making in E-commerce.

Besides these two essays, we conduct another study of dynamic decision making on a special type of websites: search engines. Specifically, we collect eye movement data on a major

search engine website that includes organic, right sponsored and top sponsored sections, over a variety of search tasks, and investigate section and snippet inspection decisions that online shoppers engaged in when search for product or service information on search engine results page. We explore the impact of two types of stimuli on information processes: one is high level stimuli, i.e., textual information; the other is low level stimuli, such as snippet location, density, and section intrinsic property. The integration of newly acquired textual information with prior knowledge, and the lag effect of low level stimuli, create a context that constantly changes as decision progress. Therefore, sequential inspection decisions are dynamic and interrelated. We apply a computational cognitive model with *static utilities* and *dynamic utilities* generated from two types of stimuli to capture this preference formation process. Our results show that sponsored sections create a strong "stickiness" effect: once consumers enter these sections, they are likely to inspect more than one snippet within the same section instead of leaving immediately. In addition, the impact of snippet location on inspection probabilities varies across organic and sponsored sections. In terms of high level stimuli, descriptive information, such as product attribute or quality, decreases consumers' "stickiness" with the current section, while transactional information, such as price and promotion, has an opposite effect. The study furthers the understanding of the effect of different types of stimuli, especially the dynamic influence from snippet content, on the information seeking behavior from a consumer's viewpoint. It offers insights in designing snippet's textual information on a search engine result page with respect to the location and content of its competitors. Implications for the platform (search engines) are also quite broad – from textual result selection, to textual content pairing, to optimal blending.

Appendices

Appendix I Transition Probabilities between Middle and Upper Layer States for the Two Information Presentation Formats (with standard deviations in parentheses)

	Product Column Format				Product Row Format	
	Middle Layer Transition Matrices					
	S^1=AB	S^1=PB			S^1=AB	S^1=PB
S^1=AB	0.769 (0.021)	0.231 (0.021)	S^2=1	S^1=AB	0.746 (0.047)	0.231 (0.047)
S^1=PB	0.096 (0.038)	0.904 (0.038)		S^1=PB	0.047 (0.011)	0.953 (0.011)
	S^1=AB	S^1=PB			S^1=AB	S^1=PB
S^1=AB	0.586 (0.029)	0.414 (0.029)	S^2=2	S^1=AB	0.719 (0.036)	0.281 (0.036)
S^1=PB	0.456 (0.071)	0.544 (0.071)		S^1=PB	0.552 (0.087)	0.448 (0.087)
	S^1=AB	S^1=PB			S^1=AB	S^1=PB
S^1=AB	0.520(0.056)	0.480 (0.056)	S^2=3	S^1=AB	0.323 (0.019)	0.677 (0.019)
S^1=PB	0.451(0.013)	0.549 (0.013)		S^1=PB	0.334 (0.038)	0.666 (0.038)
	Upper Layer Transition Matrices					
S^2=1	S^2=2	S^2=3		S^2=1	S^2=2	S^2=3
0.461 (0.099)	0.244 (0.012)	0.295 (0.090)	S^2=1	0.549 (0.047)	0.161 (0.088)	0.290 (0.070)
0.225 (0.067)	0.400 (0.045)	0.375 (0.034)	S^2=2	0.204 (0.099)	0.493 (0.054)	0.303 (0.101)
0.209 (0.111)	0.446 (0.091)	0.345 (0.089)	S^2=3	0.187 (0.087)	0.496 (0.026)	0.317 (0.095)

Note: AB: attribute-based acquisition; PB: product-based acquisition

Appendix IIa Estimated Attribute Transition Matrices

product-column condition : attribute transition probabilities													product-row condition: attribute transition probabilities											
picture	price	processor	operating sys	memory	keyboard mouse	monitor	hard drive	optical drive	wireless	office software	warranty		picture	price	processor	operating sys	memory	keyboard mouse	monitor	hard drive	optical drive	wireless	office software	warranty
0.016	0.420	0.271	0.055	0.055	0.038	0.024	0.040	0.015	0.024	0.025	0.018	picture	0.018	0.584	0.175	0.048	0.033	0.041	0.030	0.031	0.011	0.010	0.012	0.008
0.424	0.004	0.370	0.068	0.024	0.019	0.023	0.007	0.026	0.017	0.007	0.011	price	0.421	0.005	0.325	0.057	0.046	0.022	0.040	0.022	0.031	0.012	0.012	0.007
0.205	0.304	0.007	0.349	0.041	0.032	0.020	0.015	0.009	0.004	0.005	0.008	processor	0.121	0.402	0.004	0.307	0.050	0.029	0.010	0.030	0.018	0.010	0.007	0.010
0.090	0.065	0.311	0.005	0.399	0.058	0.016	0.020	0.010	0.007	0.007	0.013	operating sys	0.087	0.103	0.253	0.005	0.419	0.065	0.018	0.016	0.007	0.013	0.011	0.004
0.071	0.060	0.096	0.276	0.005	0.391	0.031	0.026	0.007	0.006	0.016	0.015	memory	0.074	0.128	0.149	0.173	0.006	0.322	0.076	0.040	0.009	0.009	0.011	0.004
0.094	0.022	0.036	0.042	0.301	0.004	0.395	0.063	0.014	0.013	0.013	0.003	keyboard mouse	0.095	0.061	0.068	0.060	0.210	0.005	0.411	0.048	0.008	0.008	0.012	0.015
0.100	0.029	0.020	0.019	0.044	0.293	0.006	0.418	0.021	0.016	0.019	0.015	monitor	0.094	0.085	0.071	0.032	0.071	0.178	0.005	0.325	0.075	0.027	0.029	0.008
0.076	0.016	0.029	0.015	0.016	0.023	0.333	0.013	0.376	0.085	0.008	0.008	hard drive	0.038	0.083	0.067	0.017	0.022	0.049	0.313	0.007	0.336	0.018	0.031	0.020
0.023	0.019	0.014	0.016	0.011	0.033	0.050	0.348	0.013	0.385	0.075	0.014	optical drive	0.049	0.033	0.042	0.015	0.013	0.016	0.070	0.202	0.007	0.430	0.075	0.047
0.066	0.024	0.027	0.030	0.024	0.022	0.020	0.038	0.273	0.011	0.385	0.080	wireless	0.025	0.026	0.039	0.010	0.011	0.023	0.018	0.075	0.342	0.007	0.355	0.069
0.073	0.018	0.019	0.006	0.028	0.028	0.025	0.006	0.032	0.292	0.009	0.465	office software	0.012	0.031	0.041	0.029	0.025	0.006	0.026	0.015	0.072	0.245	0.007	0.492
0.050	0.039	0.073	0.056	0.024	0.041	0.029	0.037	0.068	0.105	0.463	0.015	warranty	0.028	0.085	0.101	0.028	0.030	0.048	0.050	0.077	0.058	0.100	0.381	0.014

Appendix IIb Estimated Product Transition Matrices

Product-column condition: product transition probabilities						product-row condition: product transition probabilities				
Label	Product 1	Product 2	Product 3	Product 4		Label	Product 1	Product 2	Product 3	Product 4
0.005	0.767	0.155	0.028	0.045	Label	0.004	0.747	0.159	0.079	0.010
0.186	0.008	0.521	0.193	0.092	Product 1	0.250	0.010	0.508	0.149	0.084
0.037	0.410	0.004	0.418	0.130	Product 2	0.037	0.339	0.006	0.499	0.120
0.007	0.157	0.308	0.008	0.520	Product 3	0.039	0.176	0.308	0.010	0.466
0.042	0.168	0.287	0.486	0.017	Product 4	0.053	0.190	0.224	0.509	0.024

Appendix III Model Estimation Test on Synthetic Data

Variables	Starting Value	Estimated Value (posterior mean)	Real Value
PI_0_S1	0.1	0.22875228	0.2
PI_MKT1_S1	0.1	0.61499769	0.5
PI_MKT2_S1	0.1	-0.45321166	-0.3
PI_0_S2	0.1	0.39564543	0.3
PI_MKT1_S2	0.1	0.47681012	0.4
PI_MKT2_S2	0.1	-0.38364839	-0.2
PI_0_S3	0.1	0.54535731	0.5
PI_MKT1_S3	0.1	0.80136447	0.8
PI_MKT2_S3	0.1	-0.61044463	-0.6
PQ_0_S1	0.1	0.66825696	0.5
PQ_MKT1_S1	0.1	0.31771122	0.7
PQ_MKT2_S1	0.1	-0.91325732	-0.8
PQ_0_S2	0.1	0.99265948	0.9
PQ_MKT1_S2	0.1	1.31265599	1.2
PQ_MKT2_S2	0.1	-0.95266036	-0.9
PQ_0_S3	0.1	0.58022575	0.8
PQ_MKT1_S3	0.1	1.15305817	0.9
PQ_MKT2_S3	0.1	-1.42524140	-1.2
TL1_S1	0.1	0.68878361	0.8
TL2_S1	0.1	-0.31458116	-0.5
TL1_S2	0.1	-0.81875761	-0.9
TL2_S2	0.1	0.32136565	0.5
TL1_S3	0.1	0.87714547	0.7
TL2_S3	0.1	0.25091591	0.2
Gamma_S1	0.1	0.84548087	0.9
Gamma_S2	0.1	1.36810117	1.5
Gamma_S3	0.1	0.90530073	1.2
Rho_S1	0.1	0.55360011	0.5
Rho_S2	0.1	0.78094405	0.7
Rho_S3	0.1	0.80169427	0.9
Sigma[1]	0.1	0.26430815	0.2
Sigma[2]	0.2	0.49261638	0.4
Sigma[3]	0.1	0.50207708	0.4
Sigma[4]	0.2	0.69167942	0.7
Sigma[5]	0.1	0.60207708	0.8
Sigma[6]	0.2	1.04969463	1.0
V_theta[1,1]	1.0	0.98644001	1.0
V_theta[2,2]	1.0	1.05860775	1.0
V_theta[3,3]	1.0	1.02430815	1.0
V_theta[4,4]	1.0	0.89679048	1.0
V_theta[5,5]	1.0	0.95966898	1.0
V_theta[6,6]	1.0	0.91105910	1.0

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