Brand Search

Brand Search

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Chapter 1

Introduction

1.1 Motivation

Consider a shopping trip for groceries to the supermarket. You listed the groceries you need, among them the coffee brand you aim to buy. Once in the store, the only thing you need to do is to locate the groceries that are on your list. In front of the coffee shelf, you look for a red package, since the brand you search for is red, as you recall. However, the majority of the packages on the shelf contain red elements and this does not help. Thus you scan the shelf differently by starting at the left and focusing on each and every brand systematically, as if you are reading. This daily task of localizing a target brand from a spatial display of competing brands is what we define a brand search task. This task can be performed, as in the previous example, in front of a shelf, but also in a magazine, in the yellow pages, in mailorder catalogues, in retail feature ads, or in front of a computer screen, when being on the Internet.

Although common, brand search is certainly not a trivial task. Due to increasingly packed retail shelves, line extensions, store brands, and look-alike packaging, consumers frequently get confused and are not able to find the product they are looking for. Based on a nationwide survey in the US, Kurt Salmon Associates (2004) reports that 40% of the consumers say they find it hard to locate what they want. This has important implications for retailers, as the same research demonstrates that the most important reasons for consumers' dissatisfaction with retailers are all related to speed and the ease of finding what they want. These implications are underlined by the results of a recent study by Sun Microsystems (2004). In a national representative survey they find that 91% of American customers walk out of the store and shop elsewhere when they cannot find the product they want.

Not only retailers, but manufacturers suffer as well when consumers are not able to find their brands quickly. The Economist (2005) states that when consumers do not find a product within 6 seconds, they may not buy it. This has led manufacturers to invest in expensive package (re)design processes, and advertising campaigns to increase findability of their products. Kimberly-Clark for example, recently fully restyled their Kotex brand products after consumers complained that the feminine care aisle is a confusing place to shop (Acevedo 2005). They supported their new package rollout by a 360-degree marketing campaign, including television and print-advertising, in-store promotions, and an online campaign.

Even though brand search is a daily challenging task for consumers, and its outcomes may have major implications for retailers and manufactures, research in marketing on brand search has been remarkably limited. The few studies in marketing literature that deal with this topic, mostly investigate the consequences of the brand search task, rather than the process itself. For example, Drèze, Hoch, and Purk (1994) in an important study find in a field experiment that relocating cereals, juices, and bath tissues among others on the shelf from the worst to the best location may double sales for these products. This result underlines the importance of brand search, since consumers do not buy a brand when they are not able to find it quickly. Hoyer (1984) and Leong (1993) find similar results while observing consumer shopping behavior for a common repeat purchase product. They find that consumers spend little to no time on decision making and pick up a brand quickly after minimal search. However, these studies do not investigate how consumers accomplish the brand search task.

In this dissertation, the focus is on the brand search process itself. We develop a conceptual model of how consumers execute this task, and what strategies they may use. We test the conceptual model with a statistical model that analyzes the eye movements of consumers while they are performing a brand search task. The statistical formalization of the conceptual brand search model provides detailed information of the brand search process, and relates this directly to two important search performance measures: search time and accuracy. The findings of this dissertation have implications for package design, shelf optimization, and in-store and out-of-store communication to enhance findability of brands on arbitrary product displays.

1.2 Defining Brand Search

Brand search is a special case of 'visual search', which is an extensively studied area in cognitive psychology, human factors, engineering, medicine, neuroscience and other fields (Monk 1984; Sanders and Donk 1996; Wolfe 1998). Visual search is the process of reducing spatial uncertainty about a specific target among a set of distractors (Monk 1984; Sanders and Donk 1996; Wolfe 1998). The target in these tasks can be a very simple object like a red circle, or a complex one, like a specific brand of coffee, your car keys, a person, or your wallet. The distractors are defined as all the elements on the display, not being the target. When the target and distractors are complex objects, such as faces or packages, visual search requires also the reduction of identity uncertainty next to the reduction of spatial uncertainty. In the case of brand search, the target is a specific predefined brand, and the distractors are the competing brands and products on the shelf. In brand search we call the target a brand, which may be a pre-specified SKU of a brand when that brand has different line extensions, i.e. Lay's Classic, and Lay's Salt and Vinegar flavored potato chips. Throughout this dissertation we will use the general term "brand" search, also when the task is to search for a specific SKU of the brand.

Because there is no research in marketing on brand search, it is useful to differentiate this task from somewhat related, yet different consumer tasks: decision making and information search. First, brand search differs from consumer decision-making. In decision-making the consumer selects an option from two or more alternatives which optimizes some utility function (Alba, Hutchinson, and Lynch 1991; Bettman, Luce, and Payne 1998; Hoyer 1984; Russo and Leclerc 1994). In brand search however, the consumer already knows which alternative to select and the task is to localize the selected alternative, which is the reduction of spatial uncertainty instead of optimizing a certain utility function. Brand search may therefore be a stage during the decision-making process. Consider a consumer choosing between brands of coffee. Before the decision is taken, the brands have to be localized, which is a brand search task. After the brand has been found, the consumer decides which one to buy. However, brand search may also be a separate process after a decision has been made, i.e. in the situation when you already decided at home, before the shopping trip, that you wanted to buy your favorite brand of coffee.

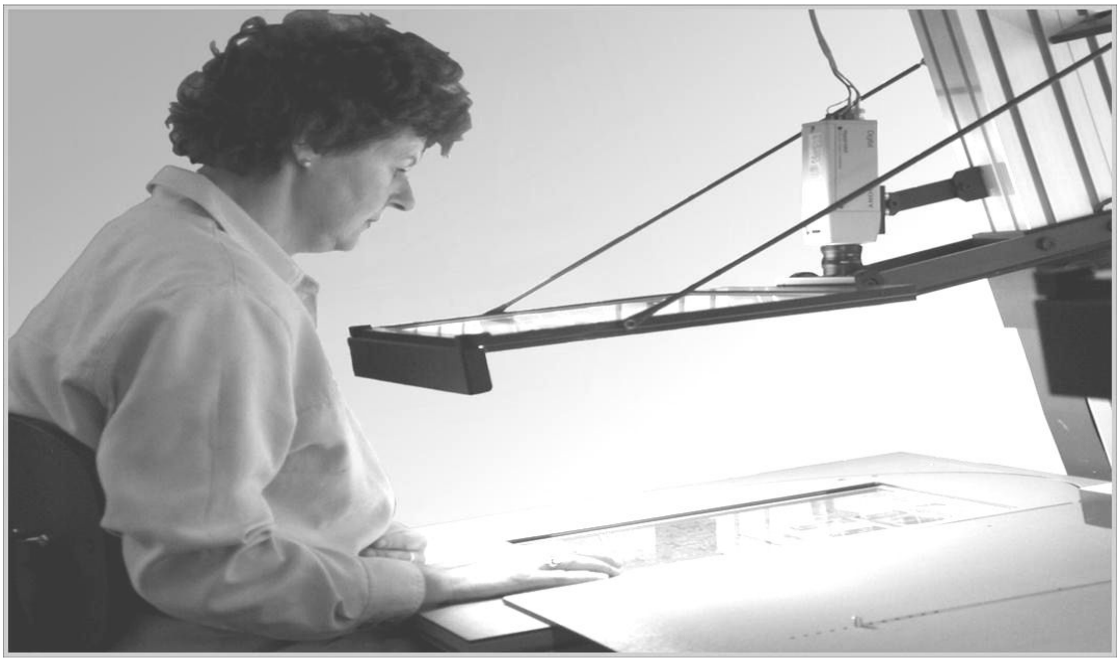
Second, brand search differs from information search as well. In information search, consumers face uncertainty about the true values of discriminating attributes of a brand (Moorthy, Ratchford, and Talukdar 1997). In order to find these values, consumers can search for this brand on the shelf and acquire the unknown information from descriptions on the package. However, a consumer may acquire these values also from other sources, such as from advertisements, salespeople, the Internet, or consumer reports. Again, similarly as in decision-making, brand search may be a stage of the information search process, i.e. when a consumer needs to find the package of a brand in order to find the true values of discriminating attributes of the brand, but in many situations information about these values are already known and the brand search process is distinct from information search.

1.3 Assessing the Brand Search Process

In almost all visual search experiments in cognitive psychology, participants need to indicate whether the target is present in the display, or they need to specify its identity (for example whether the target is rotated to the left or to the right in the display) (Pashler 1998). Using this approach, there are only two measures available per search trial, i.e. reaction time (or response latency) and accuracy (Wolfe 1998). Because many different search strategies may lead to the same search performance, and the same search strategy may lead to different search outcomes, these measures are only reliable indicators for search for very simple stimuli (i.e., a red square target among blue triangles, or a target letter ‘T’ among distractor letters ‘L’) using many (several hundreds) search trials per participant (Pashler 1998). By regressing search performance measures on different task characteristics, such as the number of distractors on the display (Treisman and Gelade 1980; Wolfe 1994), or target and distractor similarity (Duncan and Humphreys 1992), researchers try to infer underlying, mediating, search processes. Inferring these underlying search processes from search performance measures seems a valid procedure for very simple stimuli (Pashler 1998; Wolfe 1998), although it has been criticized because different processes may result in the same outcome (Pashler 1998; Sanders and Donk 1996; Townsend 1990; Wolfe 1998). Moreover in natural situations such as a brand search task, where search becomes more complicated and where several hundreds of search trials per individual are unrealistic, inferring search processes and strategies from these measures is impossible (Sanders and Donk 1996; Wolfe 1998). To understand the brand search process, one ideally needs to measure the attention process directly and relate this to task characteristics and outcomes, i.e. search performance.

During a brand search task, consumers focus their attention to different packages on the shelf in order to find the target brand. This process is reflected in the eye movements of consumers, which is the most effective measure to analyze visual search in complex stimuli, such as brand search (Findlay 2005; Findlay and Gilchrist 1998; Sanders and Donk 1996). Although researchers have always been interested in observing eye movements, only recent developments in eye tracking technology, resulting in cheaper and more accurate devices, have made this methodology suitable for large scale research (Duchowski 2003; Pieters and Wedel 2004), leading to an increase of visual search experiments using eye-tracking (Yang, Dempere-Marco, Hu, and Rowe 2002). In marketing, the analysis of eye movements has recently proved to be useful as well in assisting the development of theories in, for example, brand choice (Chandon, Hutchinson, and Young 2002; Pieters and Warlop 1999; Russo and Leclerc 1994), and advertising effectiveness (Lohse 1997; Pieters and Wedel 2004; Wedel and Pieters 2000).

Figure 1.1 *Example of a consumer in the eye-tracking experiment at Verify International (Rotterdam, The Netherlands).*



In this dissertation we use eye-tracking data to analyze how consumers execute a brand search task. The data we use in this dissertation were collected by Verify International, a commercial marketing research company, specialized in eye tracking. In all experiments, a shelf with existing brands was presented on a 21-inch touch screen to a representative sample of consumers. The equipment of this company allows consumers to sit comfortable behind the screen, and to move their head freely within certain limits (see Figure 1.1). The process underlying the collected eye-tracking data is however complex and few sophisticated statistical models have been developed to describe eye movements during search tasks. In this dissertation we develop such a statistical model that infers the brand search process from the observed eye movements and the characteristics of the search display. The statistical model formalizes the conceptual model of brand search, developed in this dissertation, and derived from theories of visual search and attention in cognitive psychology and neuroscience. The developed model advances the theory and methodology of target search and provides novel insights to marketing managers on how to improve findability and visibility of their products. Further, the model can be used to analyze individual differences, and how marketing affects the search process and its outcomes.

1.4 Outline

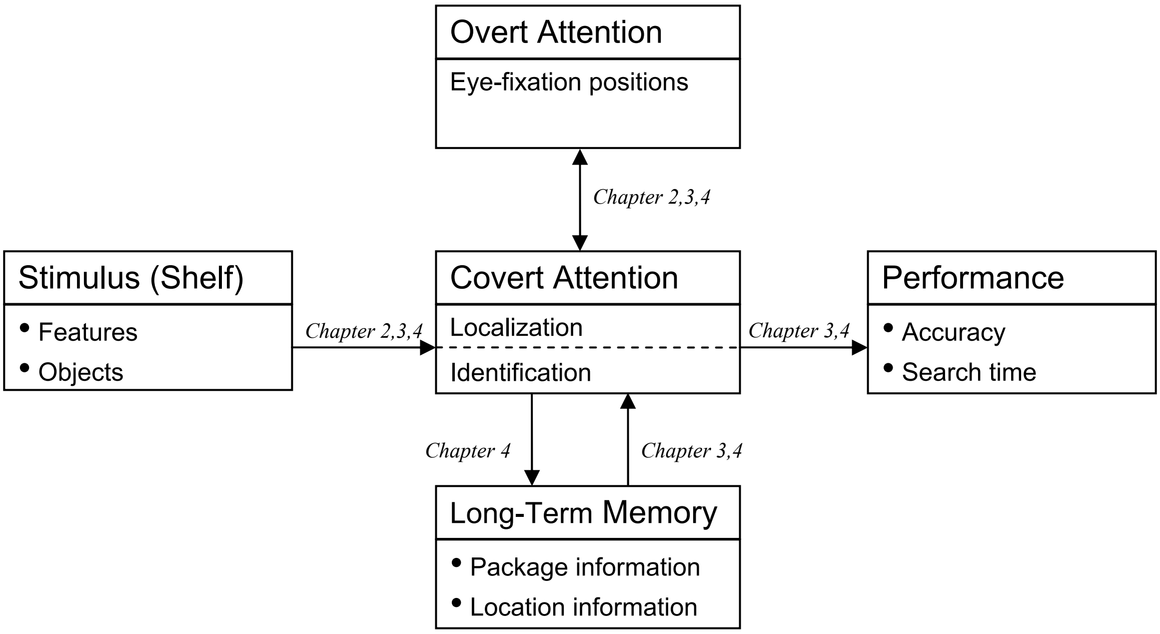
This dissertation consists of three essays that are presented in chapters 2, 3, and 4 respectively. Chapter 2 presents the first essay, which develops the basic model in a broad setting, since the model also has many important applications outside the marketing field. For example, visual search is studied in human factors to optimize search displays, such as web pages, and navigation systems, while in radiology, researchers try to understand how physicians search for bone fractions or tumors in X-rays, or how airport personnel scans luggage for potential weapons. The focus of this chapter is on the conceptualization and statistical formulation of the brand search model. This chapter concludes with an empirical application, in which the statistical model is used to describe the eye movements of consumers searching for a specific coffee brand on a retail shelf. The model finds different strategies across consumers, and the parameters of these strategies relate to the traditional search performance measures: search time and accuracy.

An important feature of the brand search model is that it enables one to estimate the salience of packages on a shelf. This feature is explored in chapter 3, where we extend the brand search model developed in chapter 2 to decompose package salience into a stimulus-based component, depending on packages and shelf-layout, and a memory-based component, depending on the search goal and knowledge of the consumer. This chapter shows that both salience components play an important role in determining the salience of packages on the shelf, which in turn influence search performance. Distinguishing these two salience components has important implications for marketing, since both components may be influenced by different marketing strategies as discussed in this chapter. Further, this chapter explores the competitive salience of the different brands on the shelf. We show that target brands may become more salient at the cost of only a few specific competitors on the shelf, and that other competitors may even benefit and become more salient as well. This interesting result turns out to be asymmetric, i.e. while brand A may gain salience from brand B when it becomes the target, the other way around is not necessarily true.

While in chapters 2 and 3 consumers search only once on a retail shelf, in reality consumers often come back to the store and search again on the same shelf. Chapter 4 investigates whether consumers use any information obtained in the first search trial in the second trial. This chapter reviews the extensive literature of memory effects in visual search, and incorporates these effects in an extended version of the brand search model developed in chapters 2 and 3. In an empirical study where consumers search twice for a specific coffee brand, we show that consumers use information of the first brand search trial in the second trial. The results show that consumers become more efficient in the second trial when an attended brand in the first trial becomes the target in the second trial. These results have both implications for marketing as well as for theories of memory in visual search.

While reading this dissertation it is important to keep in mind that chapters 3 and 4 extend the statistical formulation of the brand search model developed in chapter 2. A schematic overview of the brand search model and its extensions is presented in figure 1.2. This figure consists of five components, of which three: *stimulus*, *overt attention*, and *performance* are observed, and two components: *covert attention* and *long-term memory* are unobserved the corresponding processes taking

Figure 1.2 *Schematic overview of the brand search model*



place in the brain of the consumer. The stimulus component represents the visual information to which a consumer is exposed, in this case the shelf comprising of objects (i.e., packages), and features (i.e. colors, shapes, and brightness of the packages). Overt attention consists of the observed indicators of the latent visual attention process during the brand search task, which is inferred from the eye-fixation positions measured by the eye-tracking equipment. The observed performance component is represented by search time and accuracy. The unobserved covert attention component corresponds to the attentional process that takes place in the visual brain. This process consists of two separate states: localization and identification, based on the idea, explained in detail in the next chapter, that brand search can be decomposed into a localization problem and an identification problem. Long-term memory is the final unobserved component. This component plays an important role during brand search, as consumers may use package and location information as inputs for the covert attention process.

The brand search model in chapter 2 models explicitly the relationships between the stimulus, overt, and covert attention components, which are indicated by the arrows in figure 1.2. In chapter 3 we also explicitly model the effect of long-term memory, acquired by for example advertising and previous exposure, on the covert attention process. Next to this effect of long-term memory we also relate the covert attention process directly to search performance in chapter 3, by explicitly modeling this. Finally, in chapter 4 we test whether consumers acquire information during a brand search task, and whether they use this information in a subsequent search trial.

The final chapter summarizes the main results of this dissertation, and discusses implications for marketing and for theories of visual search. Further it discusses how the brand search model can be applied in other settings, not involving visual search tasks per se. We conclude this chapter with a discussion of limitations of this research and potential avenues for future research.

Chapter 2

Eye Movement Analysis of Target Search[1]

2.1 Introduction

Target search is one of the most common and important tasks that people perform daily. For example, radiologists search for faint nodules in chest radiographs, airplane pilots for dots on radar screens, airport security personnel for concealed weapons in x-ray images of luggage, car drivers for traffic signs, and consumers for products on overstocked shelves of retail outlets. Due to the prevalence of search tasks in daily life, since inaccuracies and slow response times can have severe implications, and because it can teach us much about primary covert attention processes, target search has a long research tradition in psychology, and other fields such as industrial engineering, human factors, and medical diagnostics (Ho, Scialfa, Caird, and Graw 2001; McCarley, Kramer, Wickens, Vidoni, and Boot 2004; Rayner 1998; Vora et al. 2002; Wolfe 1998). Such research aims at improving the selection and training of human search agents, and the organization and content of instruments and other search displays such as shelves and websites (Gramopadhye, Drury, and Sharit 1997; Wang, Lin, and Drury 1997; Yang et al. 2002). A thorough understanding of the fundamental visual attentional processes during target search and their determinants is required for those purposes, and the development of a statistical model, calibrated on eye-tracking data, to assist in that process is the goal of the present chapter.

Many studies have been devoted to inferring the covert attentional processes from response times and accuracies in search tasks (Pashler, Johnston, and Ruthruff 2001). This has proven difficult, because different attentional processes may lead to

[1] Previous versions of this chapter have been presented at the Marketing Science Conferences at the University of Maryland (2003), and Erasmus University Rotterdam (2004).

the same search performance, and the same process may produce different performances due to individual differences (Pashler 1998; Sanders and Donk 1996). Therefore, much of that research has focused on basic search tasks for abstract stimuli in simple multi-element displays, rather than on search for realistic targets in the complex scenes that people encounter daily. It is not obvious that the findings to date are generalizable to such natural situations (Bülthoff and Veen 2001; Kingstone, Smilek, Ristic, Friesen, and Eastwood 2003).

However, there is a recent surge in the scientific interest for attention to complex scenes and in the application of eye movement recording during target search on such scenes (Yang et al. 2002). Eye movements constitute process measures of covert attention with a high temporal and spatial resolution, and therefore hold the potential of yielding insights about target search that are hard to obtain otherwise (Findlay and Gilchrist 1998). The current eye tracking technology allows for comparatively large samples of individuals to be examined (Pieters and Wedel 2004), which facilitates quantitative analysis. Nevertheless, much of the previous work has relied on descriptive statistics of eye movements, and models of selected aspects of target search (Duchowski 2003; Inhoff and Radach 1998; Motter and Holsapple 2001; Rayner 1998; Zelinsky 1996). Comprehensive statistical models of the spatiotemporal attentional processes underlying target search have not been developed, despite their potential in providing a better understanding of these processes, which may at least in part be due to the complexity and computational requirements of the modeling task. In this chapter we propose and test such a model for eye movement analysis of target search.

In Section 2 we describe the theoretical foundations of that statistical model by summarizing the current state of knowledge on covert attentional processes that give rise to overt eye movements during search. Section 3 describes the data that we apply the model to; eye movements of 106 individuals who searched for a target brand in a simulated shopping environment. In Section 4, we formulate the statistical model along with the Markov chain Monte Carlo (MCMC) algorithm for its estimation. Section 5 offers the results of model estimations, and Section 6 concluding remarks.

2.2 Eye Movements for Target Search

Visual search is the process of locating a target among a set of distractors in a scene (Wolfe 1998). The target can be any visually defined object like a red square, a bone fracture, a dot on a radar screen, a splinter in a lens, or a product on a shelf. The distractors are all other objects in the scene. In real life search, targets are neither uniquely defined nor distinguished from distractors by a few perceptual features, since the distractors usually vary considerably as well. This complicates search highly, and requires attention to reduce the uncertainty in both the location and the identity of the target. *Location uncertainty* concerns where in the scene the target is located; *Identity uncertainty* concerns whether an object is the target or a distractor.

Visual search thus is an active process that invokes movements of the eyes across the spatial layout of the scene to dynamically reduce these location and identity uncertainties over time. Eye movements on stationary scenes essentially consist of fixations and saccades (Rayner 1998). Fixations are brief moments that the eye is relatively stable to project an object or region in the scene via the line of sight onto the fovea -- the small area of the retina with the highest acuity. During an eye fixation information is extracted from the perceptual field around the exact fixation position (Anstis 1974; Sanders and Donk 1996). Saccades are rapid ballistic movements of the eyes between fixation positions, during which vision is suppressed. The statistical challenge is to identify the covert spatiotemporal attention processes during target search using information on the pattern of eye fixations and saccades across the scene.

2.2.1 Attention Switching during Target Search

Since human information processing capacity is limited, efficient attentional mechanisms need to select the most behaviorally relevant information from the scene at any point in time. This involves the human brain switching between two latent states in which respectively the reduction of location uncertainty ("where") or identity uncertainty ("what") prevails (Niebur and Koch 1998). There is evidence for separate neural pathways for object location and identification, respectively the dorsal or "where" stream, passing from the primary visual cortex into the parietal lobe, and the ventral or "what" stream, terminating in the temporal lobe (Ungerleider and Mishkin 1982).

Localization State

The visual brain decomposes visual information from the scene into separate maps, representing basic perceptual features such as color, luminance, and edges. These feature maps, arising bottom-up from the scene, are processed in specialized areas of the primary visual cortex that exhibit a detailed topographic representation of the visual field (Fuster 2003). The visual brain builds a salience map of the scene as a weighted combination of the feature maps, with the weights arising top-down from specifics of the search task and knowledge of the person searching. For example, the color brown receives more weight when searching for old blemishes on apples, while indentations in the skin are important when searching for recent ones (Hillen 1984). The salience map is maintained in specialized brain structures also involved in the motor control of eye movements.

In the localization state, the salience map guides the focus of attention (FOA) to quickly select regions of the scene that contain candidate targets. Attention is deployed by visiting objects in function of their salience based on winner-takes-all and inhibition-of-return mechanisms (Itti and Koch 2001; Pomplun, Reingold, and Shen 2003).

In addition to such salience-based search strategies, attention in the localization state may be systematically guided by the scene's organization, based on a rapid visual segmentation of the search display into its constituent objects and their spatial arrangement (Wertheimer 2001). Attention is then deployed top-down by directing saccades to those scene segments (objects and locations), one-by-one, in an orderly, regular pattern (Horowitz and Wolfe 2003; Ponsoda, Scott, and Findlay 1995). For instance, Monk (1984) observed systematic horizontal zig-zag patterns (left-right and right-left) in eye movements during target search across a regular multi-element display.

These salience and systematic search strategies (Horowitz and Wolfe 2003) guide attention to locate candidate targets in the scene. Little is known, however, about the relative importance of different perceptual features in the formation of the salience map, the prominence of systematic search, and the effectiveness of these search strategies in complex scenes.

2.3. Data Description

Identification State

In the identification state of attention, the candidate object is matched to the target's representation in memory, and detailed information is sampled from it. Since complex objects in cluttered scenes cannot be identified in a single fixation, repeated fixations are required to verify their identity (Henderson, Weeks, Jr., and Hollingworth 1999). Search terminates when sufficient evidence is available for a positive match, and continues and switches back to the localization state in case of a negative match.

The proposed statistical model for eye movement analysis of target search is based on this foundation. It recognizes the spatial nature of the fixation pattern, identifies switching between the latent localization and identification attention states over time, characterizes the salience of perceptual features in attracting saccades, and represents the top-down weights given to the feature maps and systematic strategies. Before giving the details of the model and estimation, we describe the data on which it is calibrated first.

2.3 Data Description

We analyze eye-movement data collected by a commercial marketing research company in a brand search experiment. Brand search is a target search task that people engage in on a daily basis. Yet, this task often turns out to be difficult. Janoff (2001) reports that about half of the shoppers occasionally, and almost a quarter frequently fail to find a specific brand on the supermarket shelves. This has important implications, since consumers tend to chose the brand that they can find quickly (Drèze et al. 1994), which has led manufacturers to launch expensive advertising campaigns after re-branding, to help consumers locate the brand on the shelf (Plaskitt 2003).

2.3.1 Experiment

One hundred and six randomly sampled consumers participated in the experiment. Of the participants, 52% was female and 48% male; their age ranged from 16-55 years, with a median of 41 years, and none had participated in eye-tracking research before. All participants had normal or corrected-to-normal vision. Participants were instructed to search for a specific brand of coffee among a set of 12 different existing coffee brands on a computer-simulated supermarket shelf. They confirmed having found the target by touching it on the touch-sensitive screen, after which the task was completed. The instructions and search display were presented on NEC 21-inch LCD monitors, and participants were seated in front of the screen. The search display was shown full-screen at a resolution of 1,280 x 1,024 pixels in full-color mode. It contained 12 brand groups and multiple replications of each brand ("facings") in these groups (109 in total). The display was presented for a maximum of 10 seconds, which is realistic for in-store product and brand search (Hoyer 1984). During the search task, participants' eye movements were recorded with infrared corneal reflection eye-tracking methodology, with a temporal resolution of 20 ms and spatial resolution of less than 0.5º (Duchowski 2003; Wedel and Pieters 2000). The specific eye-tracking methodology allows participants to freely move their head within a virtual box of about 30 centimetres, while cameras track the eyes and head continuously. For all 106 participants, the complete pattern of fixations and saccades across time and the search display is available.

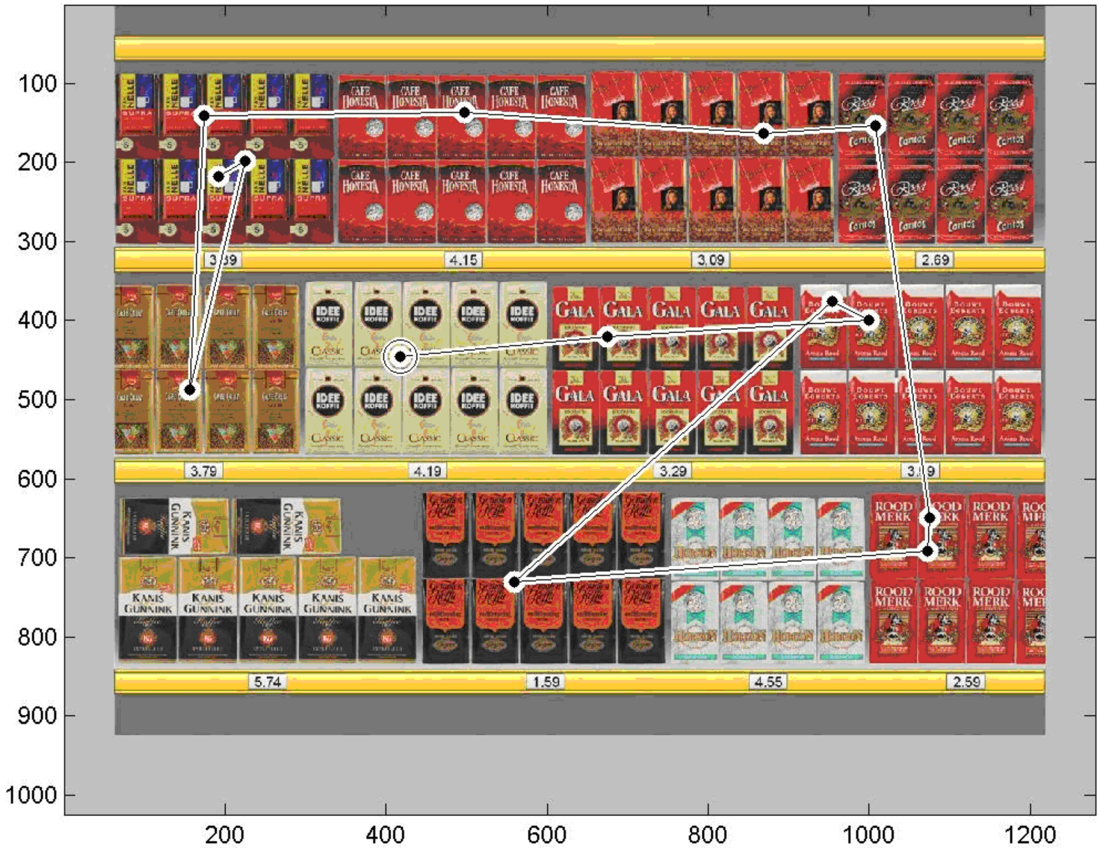
While the experiment primarily functions to illustrate the statistical model for the analysis of visual search, the computer-simulated shelf display is a realistic reflection of in-store presentations of the coffee category that people are exposed to frequently, while specialized research companies collect similar data on a regular basis for retailers and brand manufacturers. As shown in Figure 2.1, the display contains multiple brands sharing several perceptual features, such as shape and certain colors, which makes the target brand difficult to distinguish from the heterogeneous set of distractor brands, resulting in a complex search task (Duncan and Humphreys 1989; 1992).

2.3.2 Data Structure

An example of the data for a specific individual, and the corresponding eye-movement pattern is represented in Figure 2.1. The eye-movement data consist of the coordinates of the sequence of fixations and saccades between them on a LCD-computer display, which makes it possible to relate the fixations to the perceptual features of the image-pixels in the display. Because we know for each pixel its RGB-color values, and the object (here, brand-group) to which it corresponds, we define the data in terms of the characteristics of the exact fixation positions. For example, in

Figure 2.1, the first eye-fixation has *x,y* coordinates (418, 445) belonging to object number 6, with RGB-values (189, 157, 106).

Figure 2.1 *Computer-Simulated Shelf for Target Search with an Observed Pattern of Eye Movements* [a]



Fixation nr.	x	y	Object nr.	R	G	B
1	418	445	6	189	157	106
2	675	421	7	113	112	110
3	1000	400	8	192	192	192
..	..	..	..	..	..	..
13	225	199	1	51	31	59
14	192	217	1	145	56	48

The target is in the top-left of the display. An observed pattern of eye movements of a particular individual is superimposed on the display. It consists of 14 eye-fixations (dots), connected with 13 saccades (lines connecting the dots).

[a] A circle indicates starting eye fixation.

2.3.3 Decomposition of the Search Display

The search display (Figure 2.1) needs to be decomposed in sets of features and segmented objects to determine the role of the salience and systematic strategies in search. Following earlier work (Wolfe 1998), we use the basic perceptual features, color, luminance and edges (texture), and coded the 12 brand groups and the shelf as segmented objects of the image.

For each of the 1,024 x 1,280 pixels in the display the RGB-value and the object to which it belongs is known. Therefore each feature is coded as a 1,024 x 1,280 matrix, where each cell corresponds to a pixel. Objects are coded as dummy variables at the level of pixels, i.e., as one if the corresponding pixel belongs to the object, and zero otherwise. The RGB-values in each pixel are used to define color, luminance and edges. We code color features for red, gold and blue, because these colors differ systematically in diagnosticity in the current search display and task. The color red has low diagnosticity because many objects, including the target brand, share it. The colors gold and blue have high diagnosticity because few objects share it, with gold having negative (absent in target) and blue having positive diagnosticity (present in target). Colors are coded as dummy variables at the level of pixels. Luminance is computed as the weighted sum of the three RGB-values, following the NTSC and JPEG standards (Gevers 2001): $S_{\text{luminance}} = 0.299R + 0.587G + 0.114B$. The luminance values are also used to compute the edges of objects, since edges are sharp changes in luminance where visual information is dense (Parkhurst, Law, and Niebur 2002). These edges assist scene segmentation. Following Marr (1982), we define edges at locations with a maximum change in luminance, which occurs where the 2^{nd}-order derivative of luminance equals zero, and retain those corresponding to the borders of the brand groups in the display. They are coded as dummy variables at the level of pixels.

Modeling the complete sequence of fixations and saccades during target search, for a relatively large sample of people at the level of the individual pixels in the image presents an obvious computational challenge, and below we develop a complete, yet computationally tractable specification.

2.4 The Model

Let $\mathbf{S} = \{S_1, S_2, ..., S_m\}$ be the decomposition of a search display D into m separate bottom-up characteristics. Each S_k codes either a single feature, such as a color, luminance, orientation, or it codes a single object in the display that may depend on the current eye-fixation position. Consequently, the set **S** consists of two subsets: one that contains features extracted in parallel from the perceptual field by the visual cortex, purportedly used to construct the salience map. The other subset represents the objects in the display, and constitutes a segmentation of the image that is assumed to be used for the systematic strategies. Note that part of the second subset is dynamic, since it includes the previous fixation position, because the next visited position depends on it. A vector $\mathbf{s}_\ell = \{s_{\ell 1}, s_{\ell 2}, ..., s_{\ell m}\}$ containing the values of these bottom-up characteristics represents each position ℓ in the display D.

Since the extracted information declines progressively with increasing eccentricities from the fixation position ℓ^* (Anstis 1974), we assume a perceptual field that is represented by a bivariate normal distribution around ℓ^* with a standard deviation equal to ζ. Consequently, the value of S_k in location ℓ is defined as:

$$s_{\ell k} = s_{\ell k}(\zeta) = \frac{1}{\sqrt{2\pi\zeta}} \int_D s_{zk}(0) \exp\left(-\frac{\| \ell - z \|}{2\zeta^2}\right) dz\,, \tag{1}$$

where $\|\ell - z\|^{1/2}$ is the Euclidian distance between location ℓ and z, which is integrated over the whole display D. We assume a symmetric perceptual field with a width of two degrees, which is in line with prior research (Motter and Holsapple 2001; Pomplun, Reingold, Shen, and Williams 2000), and approximately the visual angle covered by the fovea (Rayner 1998)[2].

Top-down processes influence the construction of the salience map and the systematic search strategies, both of which guide attention in the localization state. In the identification state, individuals are assumed to attend repetitively to the same object to sample evidence for identification. The salience and systematic strategies are

[2] The perceptual field acts as a spatial smoother with a Normal kernel and bandwidth of 2 degrees. In principle, ζ could be taken as an estimable parameter and its conditional posterior distribution derived. However, this distribution needs to be sampled with Metropolis-Hastings methods, which proved to be computationally infeasible. Therefore, we verify our choice of ζ in the empirical application by estimating models with several pre-specified values and using model selection criteria.

represented by a collection of weights on the feature and segmented-object inputs from the search display. Let the vectors $\theta_{jc} = \{\theta_{jc1}, \theta_{jc2}, ..., \theta_{jcm}\}$ represent these top-down weights given to the set **S** by individual *c,* $c = \{1,2,...,C\}$ in state *j*, $j = \{1,2\}$ representing the localization and identification attention state respectively and that characterizes the search process. The purpose is to estimate θ_{jc} given the decomposition **S** of the display *D*, from the observed positions of the eye fixations during target search.

We introduce the vector $\mathbf{x}_{ci} = \{x_{ci1}, x_{ci2}, ..., x_{cim}\}$, which contains the values of **S** at the position of fixation *i* of individual *c*, *i* = 1,2,…,n_c. The sequence $\mathbf{X} = \lfloor \mathbf{x}_{11}, ..., \mathbf{x}_{1n_1}, ..., \mathbf{x}_{Cn_c} \rfloor$ is assumed to arise from multiple spatial point processes (Cressie 1993) over the display *D*, with intensity functions $\lambda_j\left(\theta_{jc}, \mathbf{S}\right)$. Since fixations are the realizations of a dynamic process, the likelihood of observation $\mathbf{x}_{ci}$ depends on the sequence $\mathbf{x}_{c1}$, $\mathbf{x}_{c2}$, …, $\mathbf{x}_{ci-1}$, of previous fixation positions. In addition, since eye movement patterns vary substantially between individuals (Rayner 1998), we formulate a Normal heterogeneity distribution for the individual parameters θ_{jc} with mean μ_j and diagonal covariance matrix Σ_j. Each observation $\mathbf{x}_{ci}$ is assumed to be generated by either one of two intensity functions $\lambda_j(.)$, *j* = 1,2, representing the two latent attention states -- localization and identification. We assume that individuals switch between these latent attention states according to a Markov process with transition matrix Π (Liechty, Pieters, and Wedel 2003). For each observation $\mathbf{x}_{ci}$ the total intensity function over the search display $\int_{\mathbf{S}} \lambda_j\left(s \mid \theta_{jc}, \mathbf{S}(\mathbf{F}_{ci})\right) \mathrm{d}s$ integrates to one, so that it can be interpreted as a probability density function, indicating the probability of where the FOA will be located next, given that it is generated from attention state *j*. Thus, using Scott (2002) to represent Hidden Markov Models (HMM):

$$L(\mathbf{X} \mid \theta, \mathbf{S}) = \prod_{c=1}^{C} \sum_{j_2=1}^{2} .. \sum_{j_{n_c}=1}^{2} \prod_{i=2}^{n_c} \left(\pi_{j_{i-1}, j_i} \lambda_{j_i} \left(x_{ci} \mid \theta_{jc}, S\left(F_{ci}\right)\right)\right) \tag{2.1}$$

satisfying:

$$\int_{D} \lambda_j \left(s \mid \theta_{jc}, S\left(F_{ci}\right)\right) ds = 1 \quad \forall j = 1,2 \; \forall c = 1,..,C \; \forall i = 1,..,n_c \tag{2.2}$$

where $L(\cdot)$ is the likelihood function of the sequence **X**, and $F_{ci} = \{\mathbf{x}_{c1}, \mathbf{x}_{c2}, ..., \mathbf{x}_{ci-1}\}$ is the history of observations up to fixation *i* of individual *c*. We assume, in order to identify the model, that the first fixation of each individual belongs to the localization state (i.e. $j_1 = 1$). The first fixation on the display is used to extract perceptual features and scene segments incorporated in the set **S** (Friedman 1979; Henderson et al. 1999). Therefore, **S** does not guide the first fixation, and consequently its position will not be taken into account in estimating θ_{jc}. Restriction (2.2) induces the loss of one degree of freedom, and makes one of the parameters of θ_{jc} a function of the remaining ones. We therefore express the constant θ_{jc1i} as a function of the remaining parameters so that restriction (2.2) is satisfied for every fixation (this parameter is person- and fixation-specific through F_{ci}).

2.4.1 Estimation

The model is estimated in a Bayesian framework. Here we derive the posterior distributions, from which we sample using Markov chain Monte Carlo (MCMC) techniques. We first derive the posterior distributions for the individual parameters θ_{jc} and their hyperparameters, using the auxiliary variable Gibbs sampling method introduced by Damien, Wakefield, and Walker (1999). To deal appropriately with the truncated distribution of θ_{jc} that arises naturally from our proposed link function for $\lambda_j(.)$ as described below, we use the method as suggested by Griffiths (2004). Finally, we derive the posterior distributions for the transition probabilities based on Robert, Celeux, and Diebolt (1993).

We use a square root link function, so that $\lambda_j(.) = (\mathbf{x}_{ci}\theta_{jc})^2$. This link function assures nonnegativity of $\lambda_j(.)$, while it is theoretically appealing because it formulates the spatial intensity on the surface of the display $\lambda_j(.)$ as the square of the (weighted) sum of the one-dimensional features, $\mathbf{x}_{ci} = \{x_{ci1}, x_{ci2}, ..., x_{cim}\}$. Further, contrary to the log link function (Cressie 1993, p. 655) it allows for a closed form solution for θ_{jc1i} (3), and renders the model computationally feasible. We normalize the data such that

$$\int_{\ell \in D} \left(s_{F_{c,i-1},k}(\ell) \right)^2 d\ell = 1 \ \forall k = 1,..,m \,,$$

i.e., the square of each separate perceptual feature or object integrates to one. This results in more mathematically tractable and computationally feasible formulations. We then obtain after some algebra:

$$\theta_{jc1i} = -\sum_{r=2}^{m} \left(\mathbf{s}_{F_{c,i-1}} \right)_{1r} \theta_{jcr} + \sqrt{\left(\sum_{r=2}^{m} \left(\mathbf{s}_{F_{c,i-1}} \right)_{1r} \theta_{jcr} \right)^2 - \sum_{r=2}^{m} \sum_{k=2}^{m} \left(\mathbf{s}_{F_{c,i-1}} \right)_{rk} \theta_{jcr} \theta_{jck} + 1} \,, \qquad (3)$$

with $\left(s_{F_{c,i-1}} \right)_{rk} = \int_{\ell \in D} s_{F_{c,i-1},r}(\ell) \cdot s_{F_{c,i-1},k}(\ell) d\ell$.

To avoid imaginary values for the constant, we ensure that $\sum_{r=2}^{m} \sum_{k=2}^{m} \left(\mathbf{s}_{F_{c,i-1}} \right)_{rk} \theta_{jcr} \theta_{jck} - \left(\sum_{r=2}^{m} \left(\mathbf{s}_{F_{c,i-1}} \right)_{1r} \theta_{jcr} \right)^2 < 1$. Further, to ensure unique solutions for θ, we restrict for each person c in each attention state j θ_{jc} in such a way that $\theta_{jc1i} > 0, \ \forall c, i, j$, because $\lambda_j \left(\theta_{jc}, \mathbf{S} \right) = \lambda_j \left(-\theta_{jc}, \mathbf{S} \right)$. As a result, the person-specific parameters θ_{jc} follow a truncated multivariate normal distribution with mean μ_j and diagonal variance matrix Σ_j.

We take normal conjugate prior distributions for μ_j, and conjugate Wishart priors for the covariance matrices Σ_j, j = 1,2. The hierarchical structure of the parameter vectors θ_{jc} (j = 1,2) and the priors is $\theta_{jc} \sim N_{R_c(\cdot)} \left(\mu_j, \Sigma_j \right)$, $\mu_j \sim N \left(\eta_j, \mathbf{H}_j \right)$, and $\Sigma_j^{-1} \sim W \left(\mathbf{G}_j, g_j \right)$, where $R_c(.)$ corresponds to the allowed region of θ_{jc} (see Appendix A for the determination of $R_c(.)$). Combining this with the likelihood (2.1) and using the square root link function, results in the following posterior distribution for the parameters:

$$\begin{aligned} p\left(\theta, \mu, \Sigma^{-1}, \Pi \mid x, S\left(F_{ci} \right) \right) \quad \propto \quad & \prod_{c=1}^{C} \prod_{i: z_{ci} = j}^{n_c} \left(x_{ci} ' \theta_{jc} \right)^2 \cdot p\left(\theta_{jc,-1} \mid \mu_j, \Sigma_j^{-1} \right) \cdot \\ & \cdot p\left(\mu_j \right) \cdot p\left(\Sigma_j^{-1} \right) \cdot p\left(\Pi \right) \end{aligned} \,. \qquad (4)$$

In (4), we introduce unobserved variables $z_{ci} \in \{1, 2\}$ that indicate from which attention state the fixation i of person c is generated. This is a convenient way to represent and estimate hidden Markov processes (Robert et al. 1993); the z_{ci}'s constitute a Markov chain with transition matrix $\Pi = (\pi_{j_1,j_2})$, with $\pi_{j_1,j_2} = P(z_{ci} = j_2 \mid z_{ci-1} = j_1)$.

Conditional Posterior for θ

Using (4) we write the posterior for θ_{jck} as:

$$p\left(\theta_{jck} \mid ..\right) \propto \varpi\left(\theta_{jck}\right) \cdot \prod_{i:z_{ci}=j}^{n_c} \left(l_{ci1}\left(\theta_{jc}\right) \cdot l_{ci2}\left(\theta_{jc}\right)\right), \tag{5.1}$$

with:

$$\varpi\left(\theta_{jck}\right) = \phi\left(\theta_{jck} \mid \mu_{jk}, \Sigma_{jk}^{-1}\right) \cdot I\left\{R_c\left(\theta_{jck} \mid \theta_{jc,-\{1,k\}}\right)\right\} \quad , \tag{5.2}$$

$$l_{ci1}(\theta_{jc}) = l_{ci2}(\theta_{jc}) = \left|s_{ci}(F_{c,i-1})'\theta_{jc}\right| \tag{5.3}$$

where $\phi(.)$ represents de pdf of the normal distribution, $I\{.\}$ is the indicator function and $I_{c3}\left(\theta_{jc,-1}\right)$ is the normalizing constant of the truncated distribution.

Since $\varpi(\theta_{jc,-1})$ is a truncated normal distribution, and $l_{ci1}(\theta_{jc}) = l_{ci2}(\theta_{jc}) > 0$, we apply augmented variable Gibbs sampling (Damien et al. 1999; Neal 2003). To this end, we introduce for each $l_{ci1}(\theta_{jc})$, and $l_{ci2}(\theta_{jc})$ auxiliary variables u_{jci1}, and u_{jci2} drawn uniformly from the intervals $\left[0, l_{ci1}(\theta_{jc})\right]$ and $\left[0, l_{ci2}(\theta_{jc})\right]$. Given the values of these auxiliary variables, the individual parameters θ_{jck}, $k = 2...m$, are drawn sequentially from truncated normal distributions (Robert 1995) on the region $R_c\left(\theta_{jc,-1}\right)$ satisfying the following restrictions:

$$\max\left\{u_{jci1}, u_{jci2}\right\} < l_{ci1}(\theta_{jc,-1})\ \forall\, i : z_{ci} = j \tag{6}$$

Since it is relatively easy to assess whether the restrictions in (6) are satisfied, we use the sliced sampling scheme as described in Neal (2003) and applied in Frey (1997) to avoid computation of the exact truncation points.

Conditional Posterior for μ and Σ^{-1}

Deriving the conditional posterior for μ_j and Σ_j^{-1} is challenging because the normalizing constant arising from the truncation depends on μ_j and Σ_j^{-1} (Boatwright, McCulloch, and Rossi 1999; Gelfand, Smith, and Lee 1992). As proposed by Griffiths (2004), we solve this problem by introducing a set of latent variables ϑ_{jck} that are drawn from the non-truncated distribution $N\left(\mu_j, \Sigma_j\right)$ and that have a direct (deterministic) relation with the truncated variable θ_{jck}, derived from applying the inverse distribution function transform:

$$\vartheta_{jck} = \mu_{jck} + \sigma_{jk} \cdot \Phi^{-1}\left(\frac{\Phi\left(\frac{\theta_{jck} - \mu_{jk}}{\sigma_{jk}}\right) - \Phi\left(\frac{a_{ck}\left(\theta_{jc,-\{1,k\}}\right) - \mu_{jk}}{\sigma_{jk}}\right)}{\Phi\left(\frac{b_{ck}\left(\theta_{jc,-\{1,k\}}\right) - \mu_{jk}}{\sigma_{jk}}\right) - \Phi\left(\frac{a_{ck}\left(\theta_{jc,-\{1,k\}}\right) - \mu_{jk}}{\sigma_{jk}}\right)}\right) . \tag{7}$$

In (7), $a_{ck}\left(\theta_{jc,-\{1,k\}}\right)$ and $b_{ck}\left(\theta_{jc,-\{1,k\}}\right)$ are the upper and lower truncation points respectively, corresponding to the region $R_c\left(\theta_{jck} \mid \theta_{jc,-\{1,k\}}\right)$ (see Appendix A).

Using these latent variables, ϑ results in the following standard conditional posterior distributions for μ_j and Σ_j^{-1}:

$$\mu_j \mid \ldots \sim N\left(Q_j\left(\Sigma_j^{-1}\sum_{c=1}^{C}\vartheta_{jc,-1} + H_j^{-1}\eta_j\right), Q_j\right), \tag{8}$$

$$\Sigma_j^{-1} \mid \ldots \sim W\left(\left(\sum_{c=1}^{C}\left(\vartheta_{jc,-1} - \mu_j\right)\left(\vartheta_{jc,-1} - \mu_j\right)' + G_j^{-1}\right), C + g_j\right), \tag{9}$$

where $Q_j = \left(C\Sigma_j^{-1} + H_j^{-1}\right)^{-1}$ (see Appendix B for a proof of this method).

Conditional Posterior for z and Π

To determine the latent attention state of each fixation, we estimate in each Gibbs iteration the missing variables z_{ci} that follow a hidden Markov chain with transition probabilities: $\pi_{j_1,j_2} = P\left(z_{ci} = j_2 \mid z_{ci-1} = j_1\right)$. Following Robert et al. (1993) we postulate a Dirichlet prior distribution $\Pi \sim D(\Xi)$ with $\Xi = \begin{pmatrix} \xi_{11} & \xi_{12} \\ \xi_{21} & \xi_{22} \end{pmatrix}$. This results in the following posterior distributions for the z_{ci}'s and transition matrix Π:

$$z_{ci} \mid \ldots \sim B\left(\frac{\pi_{z_{c,i-1},1} \cdot \left(x_{ci}'\theta_{(j=1),c}\right)^2 \cdot \pi_{1,z_{c,i+1}}}{\sum_{j=1}^{2} \pi_{z_{c,i-1},j} \left(x_{ci}'\theta_{jc}\right)^2 \pi_{j,z_{c,i+1}}}, \frac{\pi_{z_{c,i-1},2} \cdot \left(x_{ci}'\theta_{(j=2),c}\right)^2 \cdot \pi_{2,z_{c,i+1}}}{\sum_{j=1}^{2} \pi_{z_{c,i-1},j} \left(x_{ci}'\theta_{jc}\right)^2 \pi_{j,z_{c,i+1}}} \right), \tag{10}$$

$$\Pi \mid \ldots \sim D\begin{pmatrix} \xi_{11} + \sum_{c=1}^{C}\sum_{i=2}^{n_c} I\{z_{ci-1}=1\} \cdot I\{z_{ci}=1\} & \xi_{12} + \sum_{c=1}^{C}\sum_{i=2}^{n_c} I\{z_{ci-1}=1\} \cdot I\{z_{ci}=2\} \\ \xi_{21} + \sum_{c=1}^{C}\sum_{i=2}^{n_c} I\{z_{ci-1}=2\} \cdot I\{z_{ci}=1\} & \xi_{22} + \sum_{c=1}^{C}\sum_{i=2}^{n_c} I\{z_{ci-1}=2\} \cdot I\{z_{ci}=2\} \end{pmatrix}, \tag{11}$$

with $B(.)$ the binomial distribution.

The MCMC is run with a burn-in of 10,000, after which we keep 2,500 target draws thinned 1 in 2 for inference. Convergence is monitored using standard methods. Label switching was not observed, since the two hidden Markov states are differently parameterized (Frühwirth-Schnatter 2001). Test runs on synthetic data reveal that the chains converge well before the burn-in and recover the underlying parameters within twice the posterior standard deviation. We use diffuse priors: $\eta_j = 0$, $H_j = \text{diag}(1000)$, $G_j = \text{diag}(1)$, $g_j = m_j + 2$, and $\Xi = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$. Thus, our model presents a comprehensive, yet computationally feasible description of eye movements during target search, and allows for inference on the covert attentional process, and its determinants from them.

2.5 Results

2.5.1 Salience and Systematic Search

Table 2.1 presents the parameter estimates underlying the feature and salience maps, as well as those representing systematic search, in the localization state [3]. The color red is the "category code" being shared by most brands in this category,

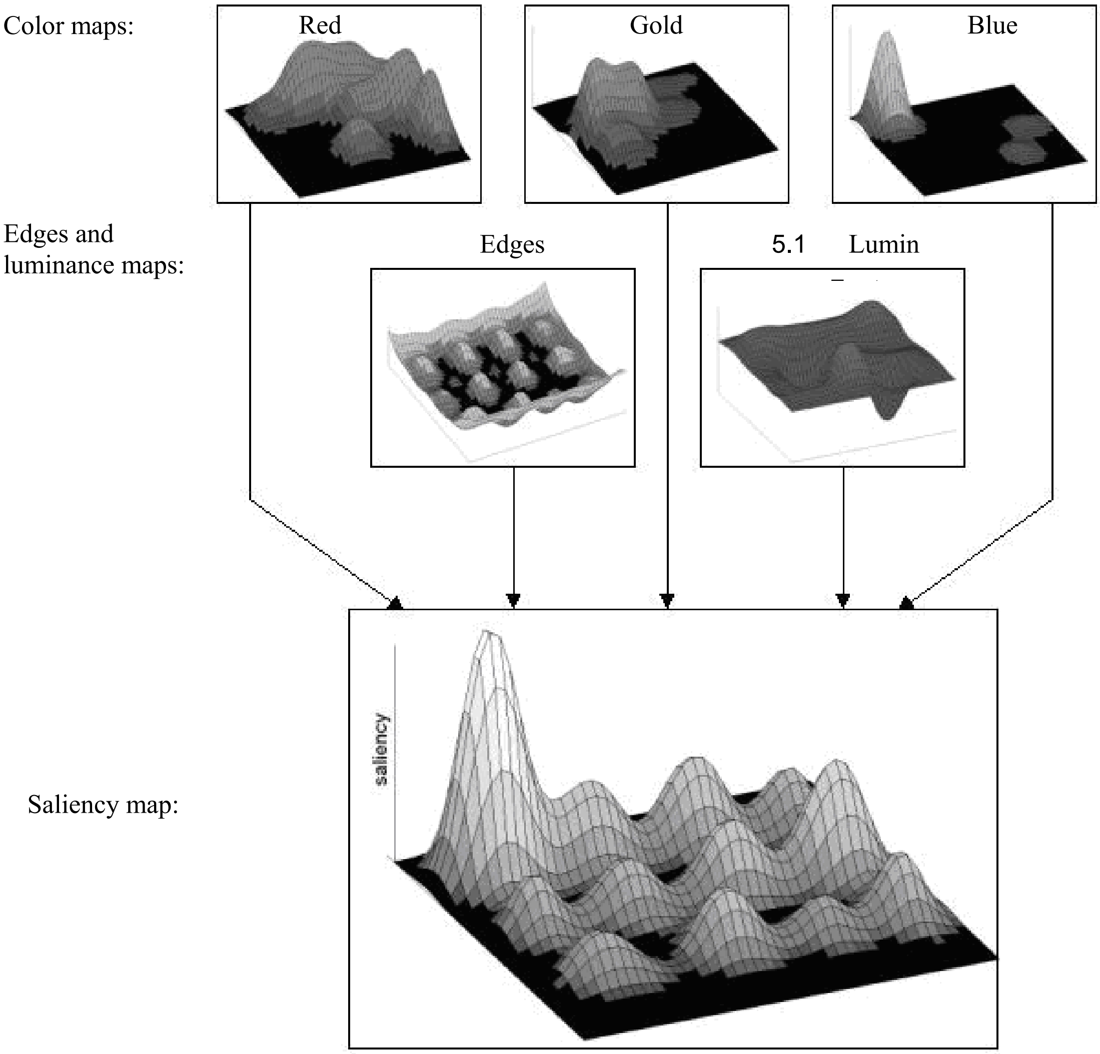
[3] We investigated the assumption about the perceptual field's size being 2 degrees by estimating models with a range of values of ζ, using DIC (Spiegelhalter, Best, Carlin, and Linde 2002). The DIC statistic is relatively flat between 1 and 2 degrees, but is minimal at the latter value: $\zeta = 0.5$: DIC = 45,013; $\zeta = 1.0$: DIC = 39,815; $\zeta = 1.6$: DIC = 38,594; $\zeta = 1.8$: DIC = 38,112; $\zeta = 2.0$: DIC = 37,828; $\zeta = 2.3$: DIC = 39,988, which supports our choice.

Table 2.1 *Parameter Estimates of Overall Means and Variances for Search Strategies: Median and Credible Intervals*

	mean(θ)			$std(\theta)$		
	Percentiles			Percentiles		
Parameters	0.025	0.500	0.975	0.025	0.500	0.975
Localization state						
Salience						
1. Color:						
Red	0.07	0.28	0.39	0.12	0.14	0.16
Gold	0.01	0.17	0.29	0.12	0.14	0.17
Blue	0.20	0.26	0.31	0.11	0.12	0.14
2. Luminance:	-0.48	-0.20	0.02	0.13	0.15	0.18
3. Edges:						
Brand group	-0.77	-0.58	-0.42	0.14	0.17	0.20
Display	0.46	0.75	1.05	0.14	0.17	0.20
Systematic						
Horizontal zigzag:						
Left-right	0.28	0.33	0.38	0.11	0.13	0.15
Right-left	0.27	0.32	0.38	0.10	0.12	0.14
Identification state						
Repetition	0.92	0.95	0.97	0.03	0.05	0.08

including the target (see Figure 2.1). Its median equals 0.28 and its credible interval does not cover zero indicating that participants used the category code to guide the FOA. Similarly, the posterior median of the positive diagnostic color blue (present in target) equals 0.26, and all posterior draws for this parameter are positive. Also, the negatively diagnostic color gold (absent in target) appears to guide the FOA as indicated by its posterior median of 0.17, although its effect is weaker compared to the colors that are present in the target, i.e. red and blue. The negative posterior median for luminance (-0.20) shows that the FOA is directed to the darker areas of the display. However, the posterior medians of the standard deviations of the distribution of the parameters across participants indicate substantial heterogeneity of feature

Figure 2.2 *Estimated Aggregate Feature and Salience Maps*



maps among participants. This indicates that participants differ in the top-down weights they place on the perceptual features to locate the target, and that they probably retrieve different representations of the target.

Using the posterior medians of the parameters for the perceptual features, we derive for each individual participant a salience map. Figure 2.2 presents the aggregate salience map and the feature maps on which it is based. Table 2.2 presents the relative salience of each brand-group on the shelf, which is computed as:

$$\text{relative saliency object a} = \sum_{g=1}^{N} \frac{\int_{\mathrm{a}} \lambda_1\left(s \mid \theta_{(j=1)c} = \overline{\theta_{(j=1)}^{(g)}}, \mathbf{S}\right) \mathrm{d}s}{\sum_{b \in B} \int_{b} \lambda_1\left(s \mid \theta_{(j=1)c} = \overline{\theta_{(j=1)}^{(g)}}, \mathbf{S}\right) \mathrm{d}s},$$

where the set B denotes all brand groups in the display, $g = 1,\ldots,N$ the target draws, and $\overline{\theta^{(g)}_{(j=1)}}$ corresponds to the mean of the individual parameters in draw g. Values in Table 2.2 larger than 1 correspond to objects with a relatively high salience, and values smaller than 1 to objects with a relatively low salience. Table 2.2 shows that the salience of the target brand (= 1) is high (median = 3.31). As can be concluded from this table, attention to some distractor brands, i.e., brand 4, 5, 6, 7, 9, 10, 11 and 12, is successfully inhibited, each having a salience significantly lower than 1.00. This salience effectively measures the "pop-out" of brands on shelves and the effectiveness of their package design to facilitate search.

Table 2.2 *Relative Salience of the Twelve Brands on the Shelf*

	Percentiles [a]				Percentiles		
Brand	0.025	0.500	0.975	Brand	0.025	0.500	0.975
1. Van Nelle	2.71	3.31	4.05	7. Gala	0.75	0.86	0.96
2. Café Honesta	1.03	1.18	1.35	8. Douwe Egberts	1.13	1.34	1.49
3. Olay's	0.85	1.05	1.19	9. Kanis & Gunnik	0.32	0.43	0.61
4. Cantos Rood	0.54	0.64	0.74	10. Gegro	0.52	0.66	0.85
5. Edah Café Cruz	0.36	0.63	0.85	11. Max Havelaar	0.27	0.44	0.75
6. Idee Koffie	0.40	0.62	0.85	12. Rood Merk	0.66	0.79	0.92
Shelf	1.00	1.00	1.00	Outside	0.05	0.08	0.13

[a] Values larger than 1 indicate relatively high salience, and values smaller than 1 indicate relatively low salience.

Whereas the posterior median of the display parameter is positive (Table 2.1: 0.75), indicating that people segment the scene based strongly on the shelf-layout to help guide attention, quite interestingly, the posterior median of the edge parameters corresponding to brand groups is negative (-0.58). This reveals that participants actively direct their FOA away from the edges of the brand groups and to the center of these objects. These results suggest that these two elements of the display layout are involved in segmentation of the scene (Wertheimer 2001).

Inspection of Table 2.1 further demonstrates that the FOA is also guided strongly by systematic search strategies, independent of the salience of objects in the display. That is, the two systematic search strategies (left-right, and right-left) have similarly large posterior medians of 0.32-0.33. This demonstrates the guidance of attention during target search by the scene's organization, as suggested by Monk (1984) and Ponsoda et al. (1995), and is the first evidence of systematic search independent of salience. These findings substantiate the combined use of salience and systematic strategies in target search, and the top-down weights placed on them.

2.5.2 Switching Between Attention States

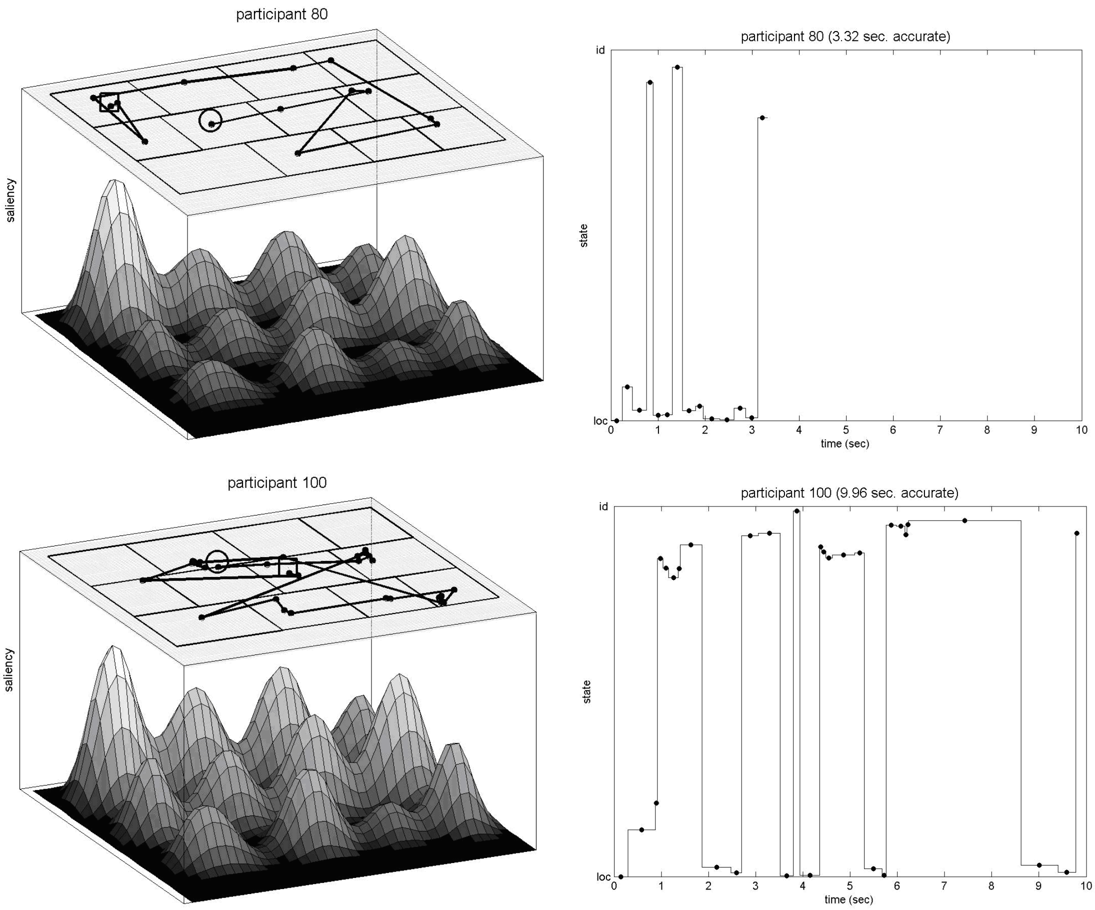
The findings in Table 2.1 reveal the importance of both covert attention states underlying target search, corroborating the findings of Liechty et al. (2003) for exploration tasks. The parameter for repetition, which indicates whether the FOA is directed repeatedly to the same object in the search display, is highly significant in the identification state (0.95) as expected. In addition, it is of interest to note that the posterior median of the standard deviation characterizing the heterogeneity of the re-fixation parameter in the identification state is quite low (0.05), only about half to one third of the heterogeneity of the parameters in the localization state, which reveals that people are homogeneous in their tendency to repeatedly fixate objects for the purpose of identification.

Table 2.3 reveals that participants are more likely to be in the localization state (median probability 0.55) than in the identification state (0.45), but still almost one half of the eye-fixations are used to reduce uncertainty about the objects' identity, which may be due to their complexity and similarities. This underscores the interest that the problem of object identification has received in recent computational models of visual search (Itti and Koch 2001), and the importance of disentangling the localization and identification state of attention.

Table 2.3 *Transition Probabilities Between Localization and Identification State of Attention*

	Localization state			Identification state		
	Percentiles			Percentiles		
	0.025	0.500	0.975	0.025	0.500	0.975
Localization state	0.46	0.50	0.54	0.46	0.50	0.54
Identification state	0.57	0.62	0.67	0.33	0.38	0.43
Limiting probabilities	0.51	0.55	0.59	0.41	0.45	0.49

Figure 2.3 *Switching between Localization and Identification and Estimated Salience Maps of Two Participants* [a].



Participant 80 (top panels) accurately located the target in 3.22 sec, while participant 100 inaccurately located a distractor in 9.96 sec. The estimated salience maps demonstrate that the target pops-out for participant 80 but not for participant 100.

[a] A circle indicates starting eye fixation, and a square indicates the last eye fixation.

Table 2.3 indicates participants' switching between attention states. The probability of switching from localization to identification is significantly lower (posterior median is 0.50), than the reverse (0.62). To illustrate attention switching during target search over time, switching patterns of two different participants are shown in Figure 2.3, along with their pattern of eye movements and estimated salience maps. It illustrates the large individual differences in attention switching over time, as well as in the salience maps.

It is instructive to examine the median fixation durations during the two attentional states. Table 2.4 shows that median fixation durations in the localization state (M = 252 ms) are significantly longer than the median fixation durations in the identification state (M = 211 ms). This difference in fixation durations is in accordance with research showing that fixation durations during scene perception (localization) are significantly longer than during reading (identification) (Rayner 1998), and consistent with our findings about re-fixations in the two attention states. Participants re-fixate more often but with shorter durations in the identification state to sample details, and they re-fixate less but with longer durations in the localization state to extract more general, feature information about the objects.

Table 2.4 *Mean Fixation Durations in Localization and Identification State of Attention*

	Mean fixation durations (*ms*) Percentiles		
	0.025	0.500	0.975
Localization state (including first fixation)	245	249	252
Localization state (without first fixation)	249	252	256
Identification state	206	211	215

2.5.3 Exploring Implications of Search Strategies

To gain insight in the model's external validity we explore how the estimated parameters of the model relate to search performance, i.e., search accuracy and latency. We do this post-hoc, with (logistic) regression of the binary accuracy indicator and the log of search time to enable assessment of the validity of the model, since these variables were not used in estimating it. Eighty out of the 106 participants correctly located the target brand within the available 10 seconds. Twelve participants were still searching after 10 seconds, and the remaining 14 participants located a wrong brand within the available time. In both regressions we use the non-truncated versions of the parameter estimates that resulted from transformation (7).

The posterior median individual-level model parameters predict search performance well (R^2 accuracy = 0.63, R^2 latency = 0.40). While the systematic search strategies are important determinants of the FOA in the localization state (Table 2.1), the extent to which participants use them does not influence search latency and accuracy. These results emphasize again the importance of eye-movement analysis of target search, since qualitative different search strategies lead to the same search time and accuracy (Sanders and Donk 1996). On the other hand, participants using the diagnostic color blue in the localization state find the target significantly faster ($\beta = -0.23$, SE = 0.05) and more accurately ($\beta = 2.04$, SE = 0.55). The salience of the other two colors, red and gold, do not have a significant influence on search performance. However, the use of luminance significantly increases search time ($\beta = 0.20$, SE = 0.07) and reduces accuracy ($\beta = -1.10$, SE = 0.58). Differences in attention to edges do not influence search performance. Further, the time spent in the identification state directly relates to the time needed to complete search ($\beta = 0.14$, SE = 0.06), but not to the accuracy of search.

2.6 Discussion

Since eye movements provide measures of covert visual attention with a high spatiotemporal resolution, eye tracking provides a powerful tool to better understand visual search on complex displays, especially with modern advances in technology that enable data to be collected at unprecedented scales, in academic and commercial settings. The identification of covert visual attention processes from eye-tracking data, however, requires a statistical model as the one presented here, to enable inferences on these key attention processes from such traces of eye movements. The comprehensive yet computationally tractable statistical model presented here incorporates attention processes consistent with neural evidence about attention and based on theories of visual search in psychology. It recognizes localization and identification states of attention, and switching over time between these states during target search. It allows for a salience map driving overt eye movements and constructed from feature maps, accommodates systematic search strategies based on the layout of the display, and reflects parametric heterogeneity of individuals in each of these components.

Application of our model to the eye movements of 106 participants engaged in a visual search task allowed us to obtain estimates of the feature maps and the resulting salience map thought to be maintained in specialized areas of the brain, and to derive measures of the visual salience of complex objects consisting of conjunctions of low-level features. This --as far as we are aware of-- is the first time that such foundational concepts in target search theory have been measured quantitatively through statistical modeling. Our results support the notion that people pre-consciously, but effectively, segment the scene into constituent components and use the spatial arrangement between these to facilitate systematic search behavior. The results show a high prevalence of the localization state for participants to determine where objects are located in the display. Once they are in the identification state to determine what the selected object is, i.e., target or distractor, they tend to switch back to the localization state with high probability to continue their search. This demonstrates the complexity of the task, in which target and distractors are similar and the distractors dissimilar among themselves (Duncan and Humphreys 1989). This requires people to repeatedly switch to the identification state to determine the identity of a candidate, and switch back to continue locating new candidates when the earlier one is not the target. Rapid identification is accomplished with re-fixations of short duration. Once more, our model calibrated to eye-tracking data with a high spatiotemporal resolution identifies the activity of these states over time, presumably reflecting activity of the "where" and "what" pathways in the visual brain.

We therefore believe that the application of the proposed model leads to new insights into the attention processes underlying target search and may aid in the optimization of search displays and the training of search agents. It may contribute to studies in industrial engineering and human factors that seek to uncover efficient search strategies in order to improve search performance in terms of time and accuracy. If applied to analyze the eye movements of experts to uncover their covert attention strategies, it may be used to develop guidelines for the training of novices (Wang et al. 1997). Analyses such as the one provided in our empirical application can be used to optimize the design of search displays, including package design and shelf layout, based on estimated salience maps and the object-saliencies derived from it. As a case in point, our model allowed us to assess the salience of brands that reflects their visual pop-out, which is known to influence in-store choices (Drèze et al. 1994).

Our results may contribute to the further development of computational theories of visual search (Niebur and Koch 1998). In many cases, such computational models can incorporate more behavioral detail than a statistical model, not being hampered by the need to directly estimate the model parameters from behavioral data. But, similar to these models, our model is rooted in the biological architecture of the visual brain, while its estimation is facilitated by MCMC methodology. Whereas computational models reproduce experimental findings of visual search using simulation based on a-priori defined parameter settings, the proposed model estimates the parameters directly from eye movements observed during visual search. Thus, our statistical approach may serve to obtain the parameter inputs of computational models and complements these by providing an empirically grounded understanding of visual search.

Chapter 3

Brand Salience in Brand Search[1]

3.1 Introduction

For consumers, brand search at the point-of-purchase has become a daily challenge due to the expansion of categories, brand extensions, me-too products, copycats, and shared product codes within categories. A typical American supermarket has around 40,000 products on its shelves, while the average shopper spends only about 25 minutes on a shopping trip[2]. Thus, consumers increasingly have to face up to the challenges of finding the items of their choice, in spite of manufacturers' unremitting efforts to improve the salience of their brands through package design and advertising. Finding your favourite brand of chocolate chip cookies among the 285 on the shelf seems like having to find a needle in the haystack (Schwartz 2004). Even for a brand with such salient packaging as Campbell soup, buyers complain about having to stare at the see of red-and-white cans to find what they want (Mulvihill 2002). As a consequence of competitive clutter on the shelf, search effort rises, consumers fortuitously pick-up the wrong brands, become frustrated, or switch brands or stores, all of which erode long-term brand and retail performance. This underscores the need for brands to be salient at the point-of-purchase.

Yet, we know surprisingly little about consumers' brand search behavior, the antecedent of purchase in the store, and how this is influenced by brand salience. Studies in marketing have emphasized the influence of brand salience in choice behavior, as either stimulus or memory property (e.g., Alba and Chattopadhyay 1986;

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[1] Previous versions of this chapter have been presented at the Marketing Science Conference at the Emory University in Atlanta (2005), and at the IC1 Conference at the University of Michigan (2005).
[2] http://www.supermarketguru.com/page.cfm/284.

Drèze et al. 1994; Romaniuk and Sharp 2004; Simonson and Winer 1992). We also know little of how consumer properties, such as brand memory and search goals, and stimulus properties, in particular the visual image of the brand, simultaneously contribute to brand salience and how this determines brand search performance at the point-of-purchase (Alba et al. 1991; Wolfe 1998; Yantis 2000). This is surprising, because manufacturers heavily invest in out-of-store marketing activities, such as advertising, to increase brand salience in consumers' memory, and in-store marketing activities such as package design and displays to increase brand salience at the point-of-purchase.

This prompted the present research to focus on brand salience and examine its influence on brand search performance at the point-of-purchase. We identify perceptual features in the visual image of brands that contribute to their salience on the shelf, and determine the influence of brand salience on the ease of finding the brand among its competitors. We decompose brand salience into its two constituent sources, stimulus- and consumer-based, and analyze competitive salience effects between and within brands. The study thus aims to contribute to a better understanding of how brand salience and search performance can be managed.

Next, in section 2 we introduce a conceptual model of brand search, which is derived from psychological theories of visual search and attention. Section 3 describes an experiment in which eye-movements of about one hundred consumers were recorded while they engaged in a computer-mediated brand search task for laundry detergents, where the target brand was experimentally varied between five groups of participants. In section 4, we formalize the conceptual model of brand search into its statistical representation, accounting for the five-group design of the experiment. Section 5 offers estimation results, and the last section conclusions and implications.

3.2 Overview of the Brand Search Model

Brand search is a form of target search. In target search, people need to find a specific item among its distractors in a visual display (Wolfe 1998). The target can be specified in terms of its perceptual features, such as "find the green cylinder," or its conceptual (semantic) features, such as "find the bottle of olive oil." When the target is specified conceptually, people need to access knowledge from long-term memory about the perceptual features that distinguish the target from its distractors in the display. Brand search at the point-of-purchase is typically a conceptual task, since consumers aim to find "Bertolli Classic," or "Tide Color," and access representations of the brand's perceptual features from memory to guide them during search. Therefore, such brand search is a mixed task, both stimulus-based through the perceptual features of the items in the display, i.e., *bottom-up*, as well as consumer-based through the accessible representations in memory of the search target, i.e., *top-down*.

During brand search consumers focus attention in space and time to select brands visually (Wolfe 1998). This is reflected in eye-movements across the shelf. Introspection falls short of informing us precisely how we move our eyes across a display, and thus what we attend to over time. What we believe to be smooth movements of our eyes in fact consist of sequences of fixations and saccades. Saccades are rapid ballistic jumps of the eyes between fixations, serving to project an informative region onto the fovea (the small central area of the retina that provides high acuity vision). Information intake occurs during these short fixations (about 200-300 ms), while vision is suppressed during saccades (about 30 ms) (Rayner 1998). Eye movements are intimately linked to the underlying covert attention patterns of prime interest in search (Findlay 2005).

Brand search is easy when the target is dissimilar from all distractors on a single perceptual feature and when all distractors are similar on that feature, such as when searching for a green target among a set of homogeneously red distractors (Duncan and Humphreys 1992) –for instance for the new Heinz green ketchup. Then, focused attention may not even be needed because the target "pops-out" of the search display and is found instantaneously on the first eye fixation based on pre-attentive processes (Treisman and Gelade 1980). On most retail shelves, however, the search target shares various perceptual features with distractors, and the distractors are heterogeneous among themselves. Then, search is difficult and focused attention is required to find the target (Duncan and Humphreys 1992; Wolfe 1998). It is to this situation that our model of brand search applies in particular (although it accounts for brand "pop-out" as well). The model can be summarized in five broad propositions (see Table 3.1), which are described next.

Table 3.1 *Modelling Propositions for Brand Search at the Point-of-Purchase*

	Propositions
1	*Attention Switching*: Attention during target search switches between a localization state that determines where in the display candidate brands are, and an identification state that determines if a candidate brand is the target or a distractor.
2	*Localization State*: A salience map and the coarse layout of the display guide attention in the localization state for candidate brand selection.
3	*Salience Map*: The salience map codes for each location in the display its conspicuousness based on the perceptual features of the brands (stimulus-based, bottom-up) and the goals of the task and memory of the consumer (consumer-based, top down).
4	*Identification State*: Attention switches to the identification state in which the likelihood that a candidate brand is the target or a distractor brand is determined, through re-fixations on spatially contiguous locations.
5	*Search Termination*: Search terminates when the perceptual features of the candidate brand match the memory representation of the target brand sufficiently, and attention switches back to the localization state when they do not, until the next candidate is located or time runs out.

3.2.1 Attention Switching during Brand Search

When the target brand is not uniquely distinguished from its competitors on a single perceptual feature, such as color, luminance or edges (Wolfe and Horowitz 2004), and when competitors are heterogeneous among themselves, search is difficult because there is uncertainty whether a specific item is the target or a distractor. Then consumers need to resolve two uncertainties, i.e., spatial uncertainty, “where” in the display candidate brands are located, and identity uncertainty, “what” the candidates are -- target or distractor brand.

Resolving spatial and identity uncertainty during target search requires qualitatively distinct processes carried out by separate neural pathways in the visual cortex (Koch 2004; Ungerleider and Mishkin 1982). Spatial uncertainty is reduced by the dorsal, "Where", stream which passes from the primary visual cortex (V1), via higher-order (V2, V3, MT) visual areas, into the posterior parietal (PP) lobe that contains neurons tuned to space and motion, amongst others. Identity uncertainty is reduced by the ventral, "What", stream which passes from the primary visual cortex (V1) via the higher-order (V2, V4) visual areas into the inferotemporal (IT) lobe that contains specialized regions for the recognition of objects.

Rather than resolving spatial and identity uncertainty concurrently, the visual brain accomplishes the task serially by rapidly switching between two states of attention (Niebur and Koch 1998). That is, attention breaks down the task of finding a brand among its distractors into a rapid series of computationally less demanding, localized visual analysis problems. Proposition 1 (Table 3.1) summarizes how brand search is accomplished by switching between, respectively a localization state to reduce spatial uncertainty and an identity state to reduce identity uncertainty. How attention is guided in these two states is described next.

3.2.2 Attention Guidance: Salience Map and Display Layout

To reduce spatial uncertainty, "where" candidate brands are, a salience map, represented in the visual brain as well as by the course layout of the display guides attention (proposition 2). The salience map is a topographic map coding the visual importance or activation of all locations in the display (Koch and Ullman 1985), and thereby the likelihood that the locations contain the target brand. It provides an efficient mechanism for attention guidance during target search by shifting the focus of attention to locations in order of decreasing salience until the target is found (proposition 3).

The salience map is build-up from basic perceptual features of the locations and items in the display, mostly color, luminance and edges that are extracted rapidly during exposure to the search display. This takes place in specialized regions in the visual cortex (including areas V1-V4), one for each basic perceptual feature (Wolfe and Horowitz 2004), and the weighted combination of their individual activations forms the salience map. The salience map is presumably represented in the superior colliculus (SC) and/or the frontal eye fields (FEF) (Niebur and Koch 1998; Thompson 2005).

To the extent that an item contrasts on a perceptual feature with its surroundings in the search display it will be more visually salient. Thus, stimulus-based salience of a brand is indicated by the activation of the salience map, and arises from the weighted combination of its basic perceptual features. Much is known about the influence of stimulus-based (bottom-up) salience on attention (Itti and Koch 2001; Parkhurst et al. 2002). Yet, both bottom-up and top-down processes influence the salience map, and our model incorporates this (proposition 3). That is, to the extent that an item matches the target on perceptual dimensions deemed diagnostic by consumers it will be more visually salient. Top-down processes such as search goals and memory for the perceptual features of the target brand, originating in the frontal cortex, modulate visual processing, even at the earliest levels (V1) (Treue 2003). This takes place by selectively enhancing visual features that are deemed to be diagnostic and by selectively suppressing features that are deemed non-diagnostic for the brand (Lee and Mumford 2003). It appears that such top-down enhancement and suppression of perceptual features is effortful and typically limited to only one or two features, for example colors (Vogel, Woodman, and Luck 2001; Wolfe et al. 1990).

Thus, the total brand salience that guides attention is the sum of bottom-up salience, derived from the perceptual features in the visual image of the brand, and top-down salience, derived from selective enhancement and suppression of perceptual features (Yantis and Egeth 1999). By decomposing brand salience into these two components, as we will do in the sequel, it becomes possible to diagnose where opportunities for improvement reside, in-store, in the visual image of the brand on the shelf, or out-of-store, such as in the brand's advertising and how this builds memory representations of brands.

Note that because salient locations may not be adjacent in the display, attention guidance by brand salience may result in a seemingly non-systematic pattern of fixations and saccades (Itti and Koch 2001; Parkhurst et al. 2002). In contrast, systematic search strategies based on the coarse layout of the display may lead to an orderly sequence of fixations and saccades across adjacent locations in the display (Monk 1984; Ponsoda et al. 1995). Consumers rapidly and pre-attentively segment search displays (Duncan and Humphreys 1992; Wertheimer 2001), based on broad organizational principles such as horizontal and vertical dimensions (Oliva and Torralba 2001). The horizontal layout of product shelves in supermarkets is an example. This facilitates search processes in which adjacent locations are sequentially fixated, until a candidate brand is located. Horizontal zig-zag (left-right and right-left) strategies have been observed in search displays, for instance (Monk 1984).

3.2.3 Identification and Terminating Search

Attention switches to the identification state to determine if a selected candidate brand is the target or a distractor (proposition 4). In the identification state, attention is guided by combinations of perceptual features, such as complex objects, logos or text, which are used to match the visual image of the brand in the display with its memory representation or prototype. This typically requires repeated fixations on small areas in the display that contain the candidate brand, and thus to shorter saccades between successive eye fixations than one would observe in the "where" state, where attention is guided by the salience map and the display layout (Bullier, Schall, and Morel 1996; Thompson 2005). Search terminates when the perceptual features of the candidate brand sufficiently match the memory representation of the target brand, and attention switches back to the localization state when they don't, until the next candidate is located or time runs out (proposition 5).

Before describing the statistical formalization, we first present the experimental data, on which the model was calibrated.

3.3 Experimental Data

3.3.1 Stimuli, Participants and Procedure

Eye movements were collected of a random sample of 109 consumers (47 males and 62 females between 16 and 55 years of age) during a computer-mediated brand search task for laundry detergents. Participants were randomly selected from the population by a professional market research agency and were paid the equivalent of 15 US$ for partaking. Participants were individually seated behind 21-inch LCD computer screens (1,024 x 1,280) on which a shelf with six brands of laundry detergent was shown, four brands with three SKUs each and two brands with two SKUs each (16 SKUs in total, from now on called "brands"). Multiple replications (facings) of SKUs were present to mimic regular shelves at the point-of-purchase, as shown in Figure 3.1.

Figure 3.1 *Example of a Search Display*

Participants were randomly assigned to one of five conditions of a one-factorial between-subjects design, in which they searched for one out of five different brands, respectively Witte Reus Tablets, Omo Tablets, Persil Tablets, Sunil Tablets, and Dixan Tablets. The sixth brand, Ariel, is the market leader in the laundry detergent category and serves as a baseline. Location of the brands in the display was rotated across conditions and consumers to eliminate possible location effects. This experimental set-up makes it possible to decompose total brand salience into its stimulus (bottom-up) and consumer (top-down) components, as described later. Figure 3.1 shows an example of the search display.

Participants had a maximum of 10 seconds to find the target brand, which is representative of search for fast-moving consumer products (Hoyer 1984; Leong 1993). They indicated having found the target brand by touching it on the touch-sensitive LCD screen, after which the brand search task ended, and they participated in unrelated other tasks. Both latency and accuracy of search were recorded.

During the brand search task, infrared corneal eye-tracking equipment sampled the participants' eye fixation positions on the display with a temporal resolution of 50 Hz and spatial resolution of 0.5° (Duchowski 2003). The specific

Table 3.2 *Descriptive Statistics*

		Target Brands During Search				
	Overall	A Witte Reus	B Omo	C Persil	D Sunil	E Dixan
N consumers	109	19	13	24	24	29
N fixations	1,762	255	186	458	378	485
Search:						
Time, *M* sec.	3.82	3.23	3.71	4.19	3.80	3.96
(*SD*)	(2.02)	(1.63)	(1.67)	(2.26)	(2.07)	(2.17)
Accurate	88 %	89 %	92 %	88 %	79 %	93 %
Out of time	3 %	0 %	0 %	4 %	4 %	3 %
Inaccurate	9 %	11 %	8 %	8 %	17 %	3 %
Features:						
% Blue	10 %	10 %	29 %	4 %	33 %	19 %
% Green	12 %	4 %	13 %	32 %	11 %	4 %
% Red	11 %	1 %	21 %	18 %	13 %	26 %
M Luminance	0.56	0.60	0.58	0.60	0.50	0.53

Note: Colors are coded as dummy variables. Luminance is normalized between zero and one, with higher values corresponding to higher luminance.

equipment allows participants to move their head freely within a virtual box of about 19 inches, while cameras record their eye movements. Distance between the eyes and the LCD screen was about 55 cm, so that all brands were clearly visible. The complete sequence of eye fixations and saccades for all participants was retained for further analysis. Summary information about the experimental conditions and the target brands is presented in Table 3.2.

3.3.2 Data

In the statistical formulation of our model, we directly relate the perceptual information in the visual image, containing the brands in the display, to the likelihood of fixating them with the eyes during the search task, on a pixel-by-pixel basis. We use information about the basic features, color, luminance and edges (Regan 2000) for each pixel in the 1,024 x 1,280 display.

Color and luminance were derived from the RGB-values of each pixel (Gevers 2001). Following NTSC and JPEG standards, luminance was derived as: $S_{\text{luminance}} = 0.299R + 0.587G + 0.114B$. Because hue intensities are highly collinear with luminance, the colors red, green and blue were coded as dummy values. These three colors are diagnostic for the category under study, and have direct managerial implications for brand and package design. The visual brain uses edges to segment search displays into relevant groups and objects. Edges are most frequently extracted from the image using procedures based on the gradients of luminance (Marr 1982). We used edges to determine for each pixel to which brand (multiple items of single SKU) and which SKU it belonged.

The region from which useful information can be extracted is larger than the exact pixel on which the eye fixates (Rayner 1998). Because the extracted information around the central fixation point can be approximated by a bivariate normal distribution (Motter and Holsapple 2001; Pomplun et al. 2000), we spatially smoothed the image data for each of the perceptual features by a two-dimensional Normal kernel. We used a bandwidth of 2 degrees which is the visual angle covered by the fovea (Rayner 1998).

3.4 Formalizing the Brand Search Model

3.4.1 Notation

Let S_c^M indicate the value of the perceptual features in all possible locations of the search display, for each consumer $c = 1,..,C$. The dimensions of S_c^M equal $\left[A \cdot B \times M\right]$, where $A \cdot B$ indicates the size of the display (in this case 1,024 x 1,280 pixels), and $m = 1,..,M$ the total number of perceptual features. Further, let S_c^D contain in a similar way the (edge-based) surfaces of the SKUs of the brands on the display for each consumer *c*. The dimensions of S_c^D are $\left[A \cdot B \times D\right]$, with $d = 1,..,D$ indexing the SKUs of the brands on the search display (in this case $D = 16$). Further we define $S_c = S_c^M \cup S_c^D$. Note that S_c is consumer-specific due to the randomization of the search display. Using S_c we define the model variables $k = 1,..,K$ that can be grouped in three sets of variables ($K = K_m + K_s + K_t$); the sets indexed by $k_m = 1,..,K_m$ containing perceptual features (input for the salience map), $k_s = 1,..,K_s$ variables representing the segmentation of the display (input for the systematic strategies), and $k_t = 1,..,K_t$ edge-based brand surfaces (to be used in the identification state). Note that the variables corresponding to K_s and K_t are a function of the immediately preceding eye fixation, because the next fixated brand-location depends only on the previously attended one, both in the systematic search strategy, and in the identification state. Because these only depend on the previously fixated location stored in spatial working memory (Lee and Mumford 2003), systematic search during the localization state and repeated fixations during the identification state can be summarized by Markov switching matrices W_s and V_t respectively, with $s = 1,...,S$ indicating the systematic search strategies (in this application $S = 2$ representing left-right, and right-left zigzag strategies, Monk 1984), and $t = 1,...,T$ different types of repeated fixations (in this application $T = 2$ representing repeated fixation on the same SKU and repeated fixation on any SKU of the same brand). The dimensions of W_s and V_t are $[D \times D]$. The value of variable *k* at location (*a,b*) of the search display is denoted as $s_{cik}(a,b)$, and defined as follows:

$$s_{cik}(a,b) = \begin{cases} S_c^M(a,b,k) & \text{if} \quad k = k_m \\ S_c^D\left(a,b,W_s\left[q\left(a_{c,i-1},b_{c,i-1}\right),q\left(a,b\right)\right]\right) & \text{if} \quad k = k_s \\ S_c^D\left(a,b,V_t\left[q\left(a_{c,i-1},b_{c,i-1}\right),q\left(a,b\right)\right]\right) & \text{if} \quad k = k_t \end{cases}, \qquad (1)$$

where $q(a,b)$ indicates the brand at location (*a,b*), and $\left(a_{c,i-1},b_{c,i-1}\right)$ indicates the position of fixation $i-1$ of consumer *c*. In (1), s_{cik}, for $k = k_m$, is constant within consumers but differs between them because of the randomization of the shelf positions of brands between consumers. For $k = k_s$ or $k = k_t$, s_{cik} is dynamic and varies between consumers and fixations through W_s and V_t respectively. Further, we let $x_{ci} \in s_{ci}$ indicate the value of vector $s_{ci}\left(a_{ci},b_{ci}\right)$ where fixation *i* of consumer *c* is positioned, and we define $\mathbf{X}$ as the $\left[\sum_{c=1}^{C} n_c \times K\right]$ matrix representing the quantification of perceptual features, systematic search, and repetition for each consumer at each eye fixation. Now that the notation is established, we describe the model's structural part.

3.4.2 The Likelihood of the Search Process

The likelihood of the brand search model consists of two components. One component represents the brand search process, which is reflected by eye fixations. The other component is the search performance, which is the outcome of the search process. Note that in the previous chapter, the brand search model only consisted of the first component. In this section we describe the first part of the likelihood, i.e. the brand search process, which is similar to the previous chapter (section 2.4). In section 3.4.4 we describe the second part of the likelihood. The total likelihood of the brand search model is a multiplication of these two likelihood components.

Based on chapter 2, the likelihood of the brand search model is:

$$L(\mathbf{X} \mid \theta, \mathbf{S}) = \prod_{c=1}^{C} \sum_{j_2=1}^{2} .. \sum_{j_{n_c}=1}^{2} \prod_{i=2}^{n_c} \left(p_{j_{i-1}, j_i} \lambda_{j_i} \left(x_{ci} \mid \theta_{cj}, S_c, q\left(a_{ci-1}, b_{ci-1}\right)\right)\right), \tag{2.1}$$

with

$$\int_{(A,B)} \lambda_j \left(s \mid \theta_{cj}, S_c, q\left(a_{ci-1}, b_{ci-1}\right)\right) ds = 1 \quad \forall j = 1,2 \; \forall c = 1,..,C \; \forall i = 2,..,n_c \; . \tag{2.2}$$

Note that the likelihood is not defined for the first eye fixation ($i = 1$), because at or before this fixation the search display is rapidly segmented and perceptual features and brands are extracted from it to build the salience map (Itti and Koch 2001; Koch and Ullman 1985). Therefore, the first fixation is not guided by the search process and is only taken into account via $q\left(a_{c1}, b_{c1}\right)$ for the second fixation of consumer c.

Latent attention switching between localization, "where", and identification, "what", is represented by a hidden Markov formulation (Liechty et al. 2003). As indicated by the latent Markov switching probabilities $p_{j',j}$ in (2.1), each fixation is either generated in the localization state ($j = 1$) or in the identification state ($j = 2$), which reflects proposition 1 of the brand search model (see Table 3.1). Because of the Markov property, the attention state in which a fixation is generated depends only on the previous attention state. Because of equation (2.2), the function $\lambda_j(.)$ can be interpreted as a probability density function describing where the next fixation will be located in the display, given that this fixation is generated in attention state j. In the localization state ($j = 1$), this function, $\lambda_{(j=1)}(.)$, represents the salience map, controlling for systematic search strategies (proposition 2 in Table 3.1). In the identification state ($j = 2$) it represents the probability of re-fixating on the previously fixated SKU or brand, respectively, for closer inspection (proposition 4 in Table 3.1). These functions $\lambda_j(.)$ depend on consumer and state-specific weights θ_{jc}

assigned to the perceptual features S_c^M and brand surfaces S_c^D. More specifically, for a location in the display with *xy*-coordinates (a,b), $\lambda_j(.)$ is defined as follows:

$$\lambda_j\left(s_{ci}(a,b)\,|\,\theta_{jc}\right)=\begin{cases}\left(\overbrace{\sum_{k\in K_m} s_{cik}(a,b)\cdot\theta_{jck}}^{\text{Salience Map}}+\overbrace{\sum_{k\in K_s} s_{cik}(a,b)\cdot\theta_{jck}}^{\text{Systematic Search}}\right)^2 & \text{if} \quad j=1 \\ \left(\underbrace{\sum_{k\in K_t} s_{cik}(a,b)\cdot\theta_{jck}}_{\text{Repetition}}\right)^2 & \text{if} \quad j=2\end{cases}, \tag{3}$$

where $s_{cik}(a,b)$ is defined as in (1). Similar to chapter 2, $\lambda_j(.)$ is a quadratic function of features and brands, which assures that $\lambda_j(.)\geq 0$, and is conceptually appealing in dealing with intensity on a two-dimensional surface. As a consequence of restriction (2.2), making $\lambda_j(.)$ a probability density function, one parameter in each attention state is not identified, and we therefore restrict the constant θ_{cj1i} (in the localization state, $j=1$) and repeated fixations on the SKU θ_{cj1i} (in the identification state, j = 1) to be a function of the remaining parameters[3].

3.4.3 Sources of Brand Salience

There are $G=5$ different groups g of consumers in the experimental design, each one searching for a different target brand in the display. Each of the five search tasks induces different top-down weights on the salience map, which enables separating top-down and bottom-up sources of brand salience (see proposition 3 in Table 3.1). Specifically, when a search target is specified, the memory representation of the brand is primed and the salience of the brand arises as the sum of its top-down and bottom-up components. When a specific brand is not the search target, its salience is purely stimulus based (bottom-up) and is thus the same across all search tasks where it is not the target. Therefore, our between-participants design makes the decomposition

[3] For interpretability, we normalized for each consumer *c*, the perceptual features S_c^M, and SKU surfaces S_c^D, such that $\sum_A\sum_B S_c^M(a,b,m)^2=1, \forall m\in M$, and $\sum_A\sum_B S_c^D(a,b,d)^2=1, \forall d\in D$, so that the estimates of θ are comparable across variables.

between bottom-up and top-down salience feasible (see Yantis and Egeth 1999). We have for consumer c the vector of salience weights θ_{cj} that follow a normal distribution across consumers; restriction (2.2) and the quadratic specification in (3) induce a truncated Normal distribution on θ_{cj}. For the consumer-specific salience weights, θ_{cj}, we specify a normal prior distribution $\theta_{cj} \sim N(\mu_j + \tau_{jg}, \Sigma_j)$, with a diagonal covariance matrix Σ_j. This specification relates to the formulation in the previous chapter where θ_{cj} was also truncated normally distributed. However, in this chapter we decompose the mean of the distribution into two components (μ_j and τ_{jg}), while in chapter 2 we only estimated the overall mean (which equals the sum of these two components, as we had only one target). Here, the mean $\mu_j + \tau_{jg}$, consists of an overall bottom-up effect μ_j, and a group specific top-down effect τ_{jg}. This formulation implements Lee and Mumford's (2003) proposition that hierarchical Bayesian inference occurs in the visual cortex, with information from higher-order areas (here: the memory representation of the brand in the frontal cortex primed by a specific search task) acting as a prior for inference in lower visual areas (here, the weights arising from the brand's perceptual features in the salience map in the SC). For identification, we restrict the G-th effect of τ_{jg} to be the sum of other $G-1$ top-down effects, i.e., $\tau_{jG} = -\sum_{g=1}^{G-1} \tau_{jg}$. This allows us to identify μ_j, the average bottom-up salience weights across consumers.

3.4.4 Search Performance

Brand search terminates when there is a sufficient match between the perceptual features of the brand's visual image and its memory representation held by consumers (proposition 5 in Table 3.1). We relate characteristics of the covert attention process to search accuracy and speed for the brand, as an integral component of the model just described. Specifically, we model the search performance for each brand as a function of its salience in the localization state (higher salience indicates lower spatial uncertainty), the relative time in the identification state when attending to *distractor* brands (shorter duration indicates lower identity uncertainty), and the total time in the identification state when attending to the *target* brand (attending longer to the target in the identification state should lead to more accurate decisions). We model this as follows.

Search accuracy (Y^{acc}) and the *log* of search time (Y^{time}) indicate search performance. They may be correlated, where positive correlations would indicate a trade-off between speed and accuracy, and negative correlations would indicate that slower consumers are usually less accurate. We allow search performance to be influenced by functions of the attention process, in particular 1) the salience of the target brand, computed as an integral of the salience map over the target brand (excluding systematic search, i.e. $q\left(a_{ci-1},b_{ci-1}\right)$=0): $f_1\left(\theta_c,z_c\right)=\int_{\text{target}}\lambda_1\left(s\,|\,\theta_{cj=1},S_c,0\right)ds$, 2) the relative time in the identification state on a non-target SKU for consumer *c,* computed as: $f_2\left(\theta_c,z_c\right)=\dfrac{\sum_{i=1}^{n_c}\left(I\left\{z_{ci}=2\right\}\cdot\left(\sum_{d\in D_{\text{distractor}}}S_c^D\left(a_{ci},b_{ci},d\right)\right)\right)}{\sum_{i=1}^{n_c}\sum_{d\in D_{\text{distractor}}}S_c^D\left(a_{ci},b_{ci},d\right)}$, with $D_{\text{distractor}}$ representing the set of SKUs corresponding to distractor brands; 3) the total number of identification fixations of consumer *c* on a SKU of the target, computed as: $f_3\left(\theta_c,z_c\right)=\sum_{i=1}^{n_c}\left(I\left\{z_{ci}=2\right\}\cdot\left(\sum_{d\in D_{\text{target}}}S_c^D\left(a_{ci},b_{ci},d\right)\right)\right)$, with D_{target} representing the set of SKUs belonging to the target brand. Here, $z_c=\left[z_{c1},..,z_{cn_c}\right]$ indicates the state (i.e., $z_{ci}=1$ if fixation *i* of consumer *c* is generated in the localization state and $z_{ci}=2$ in the identification state, see Appendix C). In addition, we include brand dummies in the accuracy and latency equations (f_r, r = 4,…,7). For search accuracy we use a probit formulation, and define the continuous latent normal variable V that is positive for accurate observations, and negative else (Albert and Chib 1993). This leads to:

$$\begin{pmatrix}Y_c^{time}\\ V_c\end{pmatrix}|\,\beta^{time},\beta^{acc},\theta_c,\Sigma^{perf}\sim N\left(\begin{pmatrix}\beta_0^{time}+\sum_r\beta_r^{time}f_r\left(\theta_c,z_c\right)\\ \beta_0^{acc}+\sum_r\beta_r^{acc}f_r\left(\theta_c,z_c\right)\end{pmatrix},\Sigma^{perf}\right),$$

where β_r^{time} and β_r^{acc} represent the coefficients for *log* search time and accuracy respectively, and Σ^{perf} is the covariance matrix.

The model is estimated using a MCMC algorithm with auxiliary variables (Rossi and Allenby (2003); see Appendix C for details of the algorithm). Estimation is based on 25,000 draws, thinned 1 in 10, with a burn-in of 25,000 iterations. In synthetic data analyses the parameters are recovered well and the chain is stationary well before the end of the burn-in.

3.5 Results

3.5.1 Descriptive Results

Table 3.2 presents descriptive results of the 109 consumers. There were in total 1,762 eye fixations on the display during the search task. Average brand search time was 3.82 seconds (SD = 2.02), which did not vary much across the different tasks. Of the 109 consumers, 88% correctly located the target brand. Most failures were due to incorrectly locating brands (10), rather than running out of time (3). Although none of the target brands was always accurately identified, brand D (Sunil) performed slightly worse than the other brands (79% versus 88% overall). Table 3.2 also presents the distribution of the color features, i.e., blue, green, and red, and mean luminance values over the target brands in the display.

3.5.2 Attention Switching

Table 3.3 shows the Hidden Markov switching probabilities as well as the limiting probabilities of each of the two attention states. Consumers were 46 percent of the time in the localization state and 54 percent of the time in the identification state during target search. The transition probabilities indicate that consumers switch frequently between these states (with probabilities 0.46 and 0.39, respectively; 83% of the consumers (91 out of 109) terminated search in the identification state.

Identity uncertainty may even be somewhat more important than location uncertainty in search tasks, since consumers spend relatively more time in the identification state (0.54 versus 0.46, respectively, the 95% posterior credible intervals do not overlap). We speculate that this is due to the nature of the brand search on shelves. As in stores, all brands were represented by several SKUs in the search display in our experiment (e.g., Persil Tablets, Color and Gel), but target search was for a single SKU only (e.g., Persil Tablets). Different SKUs of the same brand are perceptually similar which may increase identity uncertainty, and cause

Table 3.3 *Attention Switching During Target Search: Median and 95% Credible Intervals of Transition Probabilities*

Source State:	Destination State: Localization			Identification		
	0.025	0.500	0.975	0.025	0.500	0.975
Localization	0.49	0.54	0.59	0.41	0.46	0.51
Identification	0.34	0.39	0.44	0.56	0.61	0.66
Limiting probabilities	0.42	0.46	0.50	0.50	0.54	0.58

Note: The limiting probability for the localization state is computed as: $\frac{1-p_{22}}{1+p_{12}-p_{22}}$, and for the identification state as: $1-\frac{1-p_{22}}{1+p_{12}-p_{22}}$ (see Ross (1997), p. 174).

brand confusion (Kapferer 1995; Keller 2003). In such a situation, once consumers have localized a candidate brand, more detailed exploration of the various SKUs of the brand is required to determine which of them is the target. Findings to be presented later support this.

3.5.3 Attention Guidance

Table 3.4 shows that brand salience clearly guided attention in the localization state. The positive parameter estimate of luminance (posterior median: 0.10, all posterior draws are positive) indicates that attention was directed to the brighter locations in the display. Although all colors guided attention, blue took the highest salience weight (posterior median: 0.24, all posterior draws positive). Systematic search strategies guided attention as well (posterior medians for the horizontal zigzag strategies are 0.26 for left-right and 0.24 for right-left, all posterior draws positive). These results are obtained across the five search tasks and rotated search displays in the experiment, and thus are not due to specific positions of brands and SKUs.

In the identification state, consumers either repeatedly sample information from the candidate, or by compare the candidate with other SKUs of the same brand, located contiguously on the shelf. The posterior median, 0.37, of the brand-repetition

Table 3.4 *Attention Guidance During Target Search: Median and 95% Credible Intervals*

Parameter	Mean			Standard Deviation		
	0.025	0.500	0.975	0.025	0.500	0.975
Localization State:						
Salience Search						
1. Color:						
Blue	0.16	0.24	0.34	0.06	0.08	0.12
Green	0.01	0.07	0.14	0.06	0.08	0.11
Red	0.03	0.14	0.22	0.06	0.08	0.12
2. Luminance:	0.04	0.10	0.16	0.07	0.11	0.15
Systematic Search						
Horizontal zigzag:						
Left-right	0.21	0.26	0.32	0.06	0.09	0.13
Right-left	0.19	0.24	0.30	0.06	0.08	0.12
Identification State						
Repetition:						
Brand	0.29	0.37	0.45	0.09	0.13	0.18

Note: None of the credible intervals covers zero.

parameter (see Table 3.4) reveals that consumers have a high probability of switching between SKUs of the same brand in trying to reduce identity uncertainty. Yet, consumers re-fixated even more frequently the same SKU, as shown its posterior median probability of 0.63 (=1 – 0.37, due to the restriction imposed in equation 2.2).

The qualitatively different processes that guided attention during the localization and identification state revealed themselves in the length of the saccades between eye fixations in each of the two states (Bullier et al. 1996; Thompson 2005). Saccade lengths were on average 3.4 times larger in the localization state (0.025, 0.500, and 0.975 percentile estimates are respectively 277.8, 284.4, and 291.0 pixels) than in the identification state (respectively 79.0, 83.1, and 87.3 pixels).

3.5.4 Brand Salience

We now provide a more detailed picture of the brand salience effects discussed in the previous section. When a brand becomes the target for search, its memory representation is primed and particular perceptual features will accordingly receive a higher or lower weight in the salience map, compared to a situation where the brand is not the target. Table 3.5 reveals that for each brand a single perceptual feature at most is enhanced when it is the search target, be it a particular color or luminance. This is consistent with the findings of Wolfe et al. (1990), who showed that attention cannot be guided by two different colors simultaneously during target search, even though color is one of the most efficient search features (Wolfe and Horowitz 2004). That is, for Brand B (Omo) luminance is prioritized (median: 0.28), for Brand C (Persil) the color green (median: 0.29), for Brand D (Sunil) the color blue (median: 0.17), and for Brand E (Dixan) the color red (median: 0.20). These enhanced features of brands are in fact strongly diagnostic (see lower part of Table 3.2), which reflects the brand knowledge of the consumers in the sample. Notably, no feature is enhanced for the only brand that is undifferentiated in terms of those features (brand A: Witte Reus).

Selected perceptual features are inhibited as well, and they vary across brands. For instance, for Brand D (Sunil), where the color blue was enhanced, the color red is simultaneously inhibited (median: -0.18), as is its luminance (median: -0.13). When

Table 3.5 *Consumer Source of Brand Salience*

	Target Brands During Search				
	A Wittereus	B Omo	C Persil	D Sunil	E Dixan
Color:					
Blue	**-0.27**	0.12	-0.11	**0.17**	0.09
Green	**-0.23**	-0.10	**0.29**	0.11	-0.07
Red	**-0.19**	0.14	0.04	**-0.18**	**0.20**
Luminance:	-0.06	**0.28**	-0.01	**-0.13**	-0.08

Note: Median parameter estimates are presented for space considerations. Estimates in **bold** are from 0.025 – 0.975 credible intervals not covering zero.

searching for brand A (Witte Reus = "White Giant") all three colors, blue, green, and red (median: -0.27, -0.23, and -0.19 respectively) were inhibited, which presumably reflects the color-coding and positioning of this brand. Top-down processes may thus inhibit features besides enhancing them to guide attention when in the localization state (Treisman and Sato 1990).

3.5.5 Search Performance

Table 3.6 presents the parameter estimates for the target brand's salience, the relative time in the identification state when attending to distractor brands, and the total time in the identification state when attending to the target brand, while controlling for possible other brand-specific effects through brand dummies. Since the relative time in the identification state on distractors serves as the baseline, the coefficient of the

Table 3.6 *Determinants of Brand Search Performance: Median and 95% Credible Intervals*

Predictor	Brand Search Performance					
	log (Search Time)			Search Accuracy		
	0.025	0.500	0.975	0.025	0.500	0.975
Constant	**1.12**	**1.83**	**2.75**	**-10.11**	**-5.06**	**-0.69**
Dummy brand B: Omo	**0.75**	**1.77**	**3.17**	**-18.49**	**-9.26**	**-2.80**
Dummy brand C: Persil	-0.43	-0.02	0.34	-1.13	0.93	3.27
Dummy brand D: Sunil	**0.21**	**0.71**	**1.45**	-6.68	-1.69	1.28
Dummy brand E: Dixan	**0.28**	**0.77**	**1.36**	**-8.08**	**-3.90**	**-0.90**
Brand salience	**-20.25**	**-12.17**	**-5.68**	**22.21**	**72.75**	**118.54**
Identification on non-targets [1]	-0.39	0.35	1.14	-7.14	-0.93	5.04
Identification on target brand [2]	**0.03**	**0.06**	**0.10**	-0.01	0.27	0.70
Covariance:						
log (Search time)	**0.07**	**0.13**	**0.20**	-0.11	0.18	0.36
Search accuracy	-0.11	0.18	0.36	-	1 [3]	-

Note: **Bold** credible intervals do not cover zero. [1] Proportion of fixation frequency on SKUs of competitive brands in identification state. [2] Number of identification fixations on SKUs of target brand. [3] Variance of search accuracy set to one for identification.

time in the identification state on the target brand can be interpreted as the additive search performance benefit of reducing identity uncertainty. The results show that salient brands were clearly found faster and more accurately (posterior median: -12.17 and 72.75 for (*log* of) search time and accuracy respectively). Although the relative time that consumers spend in the identification state on non-target brands did not influence search performance, the relative time on the target brand clearly does. As expected, consumers who direct more identification fixations to the target are more accurate (posterior median: 0.27, with 97% of the posterior draws positive). This accuracy gain goes at the expense of longer search times (posterior median: 0.06, with all posterior draws positive). Finally, the positive correlation (0.18) between search time and accuracy underlines the trade-off in this search task between being fast and accurate.

3.6 Conclusions and Implications

3.6.1 Intended Contributions

Consumers are remarkably apt in finding the brands they search for at the point-of-purchase, despite the challenging nature of the task. In our experiments, it took consumers on average less than four seconds to find a specific brand of laundry detergent on a cluttered shelf with fifteen visually similar distractors. To understand how consumers accomplish this and to gain insight in the role of brand salience in brand search, we proposed a model that builds on theories of visual search and attention, and contributes to that literature in several respects.

First, even though the idea of a salience map is part of most conceptual models of target search, such as Guided Search (Wolfe 1998) and Area Activation (Pomplun et al. 2003), the proposed model is the first to estimate the salience map empirically from eye-movements, rather than deriving it from local feature contrasts in the visual image itself, as has been previously done (Itti and Koch 2001). Thus, the proposed model enables one to estimate brand salience directly from the influence that perceptual features in the visual image have on attracting eye fixations, instead of deriving presumed stimulus-based salience from the visual image in a first step and relating this to the eye-movements of consumers in a separate step (Parkhurst et al. 2002). Our approach is more in keeping with the original idea of the salience map as a perceptual construct (Koch and Ullman 1985), and provides the empirical weights that perceptual features have in building up the salience map. Thereby, we obtained the importance of these features in driving the salience of brands on the shelf.

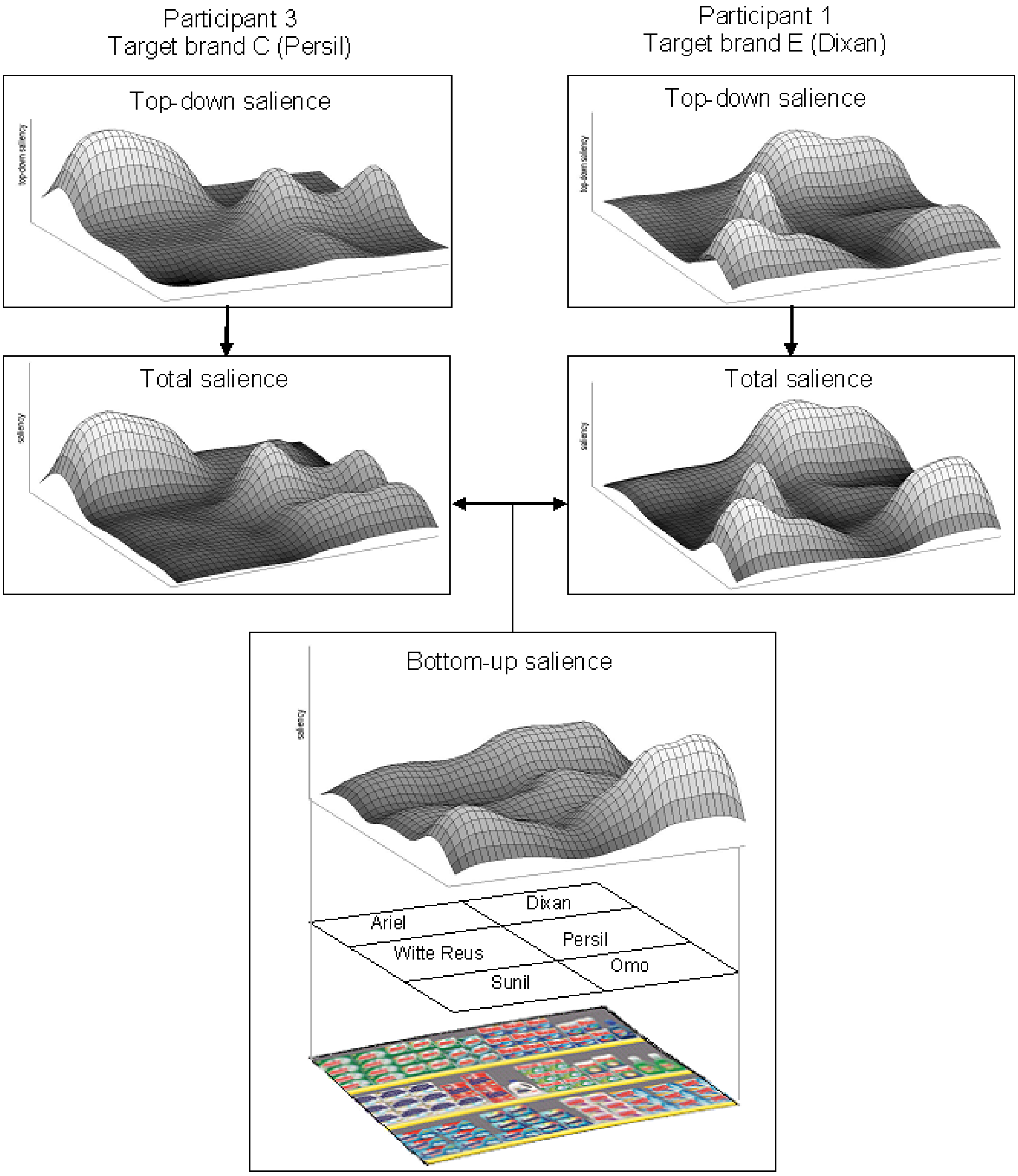
Second, to our knowledge the proposed model is the first to disentangle salience from search performance, thus avoiding conceptual circularity (Hommel 2002). That is, rather than equating salience directly with search performance as has been mostly done previously (i.e. a stimulus is salient if it is found quickly), we estimate salience based on the ability of the brand's visual image to attract eye fixations during search. The model does this on a pixel-by-pixel basis, and simultaneously estimates the influence that salience has on search performance, while controlling for other covert attention processes. Failure to account for these other processes, such as strategic search based on the shelf's layout and attention deployment to reduce identity uncertainty, would lead to biased estimates of brand salience.

Third, and most importantly, the proposed model, Bayesian inference procedures, and experimental design make it possible to estimate a salience map for each consumer and brand separately, and permit a decomposition of brand salience into its stimulus (bottom-up) and consumer (top-down) sources (cf., Yantis and Egeth 1999). This enables diagnostic analyses of the sources of competition for brand salience at the point-of-purchase, and it assists in identifying more effective strategies to improve brand salience, as shown next. We first decompose the total salience of a brand into its bottom-up and top-down sources, to examine where opportunities for improvement reside. Then, we perform a competitive analysis of visual salience to investigate how enhancing the salience of a particular SKU may simultaneously inhibit or enhance the salience of other brands and SKUs on the shelf.

3.6.2 Sources of Brand Salience

Figures 3.2 and 3.3 illustrate the implications of decomposing brand salience into its bottom-up and top-down components. Figure 3.2 shows for two participants (1 and 3) and two brands (C and E) the stimulus-based component of the salience map (bottom), the two consumer-based top-down components of the salience map (top), and the two resulting salience maps (middle). The stimulus-based salience map at the bottom of Figure 3.2 is the same across search tasks (but note that heterogeneity in the salience map across individuals is accommodated), being build-up from local feature contrasts

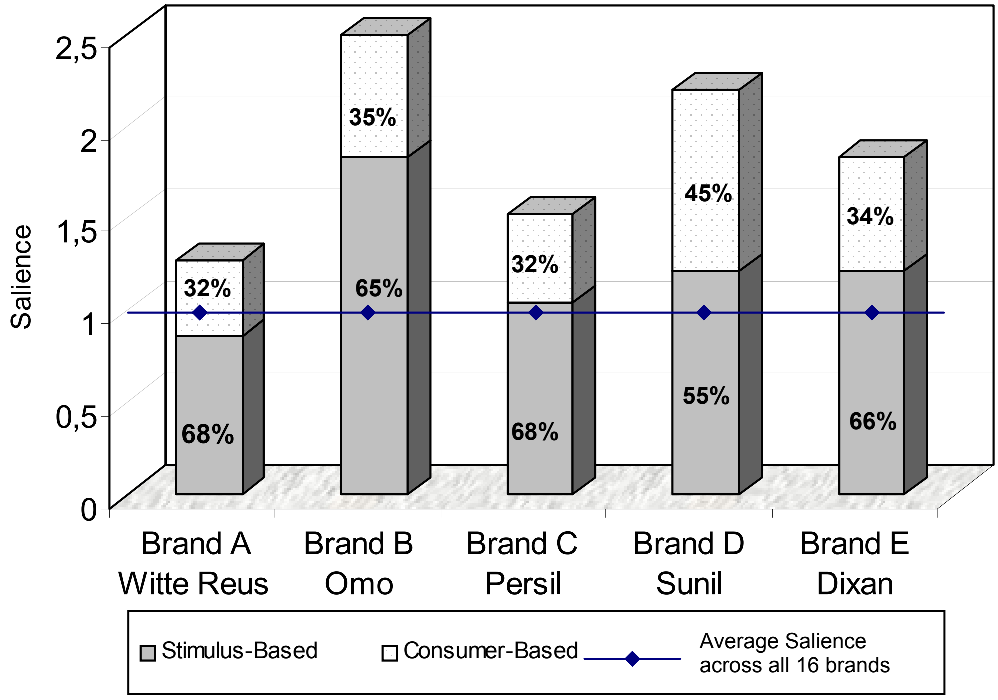
Figure 3.2 *Decomposition of Salience Map into: Stimulus (Bottom-up) and Consumer (Top-down) Sources*



(Itti and Koch 2001). The figure illustrates the dramatic effects of top-down consumer weights on the salience maps and how, using the proposed approach, inferences on salience can be made for each consumer and brand separately.

Figure 3.3 presents for each of the five target brands separately, the total salience per image-pixel and the proportion of this due to stimulus and consumer sources. For comparison, a line representing the average salience per pixel (set equal

Figure 3.3 *Sources of Brand Salience: Stimulus and Consumer*



to one) in case of a non-informative salience map is plotted. The salience map for the target brands is diagnostic, because the total salience of all target brands is higher than average. Differences in total salience between brands, as well as in their bottom-up/top-down compositions, are apparent. For instance, whereas both brand B (Omo) and brand D (Sunil) are highly salient, the salience of the first brand derives more from the stimulus (65%), its visual image in the search display, than the second brand does (55%). Overall, stimulus-based salience accounts for about two-thirds of the total salience, except for Sunil. This emphasizes the need to look at salience as arising from the interplay between stimulus and consumer sources at the point-of-purchase, rather than measuring it as a stimulus or consumer construct only. The decomposition suggests avenues for building salience through in-store activities such as packaging redesign, in order to increase the salience of the brand's visual image on the shelf, notably for brands A and D, but also through out-of-store activities such as advertising, in order to strengthen the memory representations of the brands in consumers' minds, notably for brands A, B, C and E. For package design, the presented model could serve as input to improve the salience of the brand's visual image at the point-of-purchase. For example, although Brand A, Witte Reus, is relatively salient when it is the search target, its low stimulus-based salience suggests that it hardly attracts attention in situations when it is not the target. In other words, when it is not on the consumers' shopping list, stimulus features of Witte Reus are insufficient to serve as "circuit breakers" to make the brand "pop out" for consideration. The estimated bottom-up, or stimulus-based, salience weights of perceptual features show how to improve this. A solution for this brand might be, for instance, to increase the amount of blue in the package, since this color has the highest bottom-up contribution to salience and is already moderately present in its package.

However, as packages are never presented in isolation on the retail shelf, brand salience is intrinsically relative to other SKUs from the same and different brands. While a package should not differ too much from these to be recognized as coming from a particular brand and category, at the same time it should also be sufficiently distinct in order to be salient and attract attention. Thus, visual image information of other brands and SKUs needs to be factored into decisions of package (re-) design. We therefore analyze competitive salience next.

3.6.3 Competitive Salience Effects

Brands and SKUs compete for salience on the shelf because they cannot *all* be simultaneously salient. Thus, increases in the salience of a particular brand/SKU lead to decreases in the salience of other brands/SKUs, but they may selectively enhance the salience of particular brands/SKUs as well. These competitive brand salience effects can be understood through the model estimates. Recall that we have five target brands in the experimental design, and a sixth brand, Ariel, which was not a target and is the market leader, that all brands are represented by multiple SKUs (in total 16), and that in all cases search was for one specific SKU of a brand (the "tablet" SKU). This makes it possible to assess which brands and SKUs gain or lose by the increased top-down salience when each particular brand becomes the search target, thus revealing the within and between-brand competition for salience. Table 3.7 presents the findings. The letters A to E in the rows and columns indicate the "target brand". The diagonal in Table 3.7 (highlighted) contains the "own-brand" effects, i.e., the increased salience of the brand when it is the target, which are all positive, as

Table 3.7 *Competitive Salience Analysis:Enhancement and Inhibition Effects*

Competitive Salience Effects		Target Brands During Search				
		A Witte Reus	B Omo	C Persil	D Sunil	E Dixan
A	Witte Reus Tablets	**3.05**	1.48	**-2.18**	-1.09	**-2.12**
	Color Reus	0.65	-0.76	-0.40	-1.15	**1.82**
	Witte Reus Vloeibaar	**0.45**	**0.84**	-0.22	**-0.64**	**-0.33**
B	Omo Tablets	**-7.38**	**8.03**	**-3.22**	-0.29	2.38
	Omo Color	0.41	**5.94**	-0.94	**-3.47**	-0.91
C	Persil Tablets	-0.85	0.83	**2.48**	**-1.74**	**-1.54**
	Persil Color	0.11	0.39	**0.69**	**-0.85**	**-0.72**
	Persil Gel	0.10	**-1.14**	**1.84**	0.71	**-0.66**
D	Sunil Tablets	-2.09	**-3.88**	**-2.48**	**6.40**	2.60
	Sunil Color	0.27	**-2.79**	-0.94	**3.62**	0.26
E	Dixan Tablets	-2.00	-0.90	**-2.83**	-0.64	**4.97**
	Dixan Megaperls	-0.51	-0.24	**-0.81**	0.10	**1.16**
	Dixan Gel	0.37	**-0.59**	-0.22	**0.72**	0.27
	Ariel Essential	**-1.58**	**-2.41**	**5.86**	0.02	-1.37
	Ariel Color	**-1.51**	-1.79	**5.07**	-0.15	**-1.40**
	Ariel Hygiene	**-0.56**	**-0.95**	**1.59**	-0.13	-0.38

Note: Median parameter estimates (multiplied by 100) are presented. Estimates in bold are from 0.025 – 0.975 credible intervals not covering zero.

expected. The off-diagonal effects capture competitive salience effects and are of most interest.

There is systematic evidence for within-brand crossover of salience. That is, almost universally all SKUs of the target brand gain in salience, when one particular SKU of that brand is searched for. For example, when searching for Persil Tablets (brand C) the salience of Persil Color (median: 0.69) and Persil Gel (median: 1.84) increases. This is most likely due to within-brand similarity in color/luminance (and not to their contiguous positions on the shelf, since systematic search effects are controlled for through the model formulation). This conjecture is supported by the observation that, when searching for brand A, Witte Reus Tablets, or brand E, Dixan Tablets, the salience of respectively Color Reus, and Dixan Gel did not increase significantly: these two SKUs were very differently color-coded. After our experiment was conducted we found out that the package designs of Witte Reus were changed. Clearly, too much crossover of salience might be a liability if the other SKUs gain as much or more salience than the target SKU does. This might signal insufficient differentiation between the packaging of SKUs of the same brand, and indicate confusion between the SKUs. It was common in our experiment, and only for brand E (Dixan) was the increase in salience for the target (Dixan Tablets) significantly larger than for the two other SKUs (MegaPerls and Gel).

There is also evidence for between-brand enhancement of salience. This is most remarkable for SKUs of Ariel, the market leader. When brand C, Persil, was the target it increased the salience of all three Ariel SKUs (medians are respectively 5.86 for Ariel Essential, 5.07 for Ariel Color, and 1.59 for Ariel Hygiene). This is most likely due to the similarity in color-coding between these two brands: 32% of the pixels of the Persil target SKU are green, the highest percentage of all brands -- however 40% of the pixels of Ariel are also green.

There is systematic support for between-brand inhibition of salience as well. For example, when brand A (Witte Reus) is the target, all SKUs of the market leader Ariel are inhibited, which is presumably results from its different color-coding and positioning. Both symmetric and asymmetric competition in salience occurs. For instance, symmetric competition is evident between brand B (Omo) and brand D (Sunil). When brand B (Omo) is the target its salience increased chiefly at the expense of brand D (Sunil; median reduction –3.88 and –2.79 for its two SKUs), while the opposite holds as well (Omo; median reduction: -0.29 and –3.47 for its two SKUs).

An example of asymmetric salience competition is between brand A, Witte Reus, and brand B, Omo (Tablets). The latter brand’s salience significantly reduces when consumers search for Witte Reus (-7.38), but the reverse does not occur (1.48).

Ideally, during search for a target SKU of a particular brand all other SKUs corresponding to the brand, including its line-extensions should become more salient.

The increase in salience of the target SKU however, should be greater than that of the other SKU's from the same brand. Simultaneously, competitor brands should become less salient. As the gain in salience may come from a few specific brands, a manufacturer may try to inhibit salience of its most important competitors even more to avoid brand confusion (Kapferer 1995; Kearney and Mitchell 2001). Crossover salience effects between brands need not be symmetric, which means that a brand may inhibit a competitor brand when it becomes the target, but not the other way around. This together makes optimal package design a challenging task, for which we expect analyses such as the present one to provide useful input.

3.6.4 Future Research Avenues

The model could be used in pre-testing and post-testing theme or feature ad advertising, by examining advertising effects on the (increased) top-down component of brand salience map, and the (decreased) duration of the brand identification state. Such applications of the model would reveal implicit memory effects of advertising, without explicitly probing memory (cf., Shapiro and Krishnan 2001). Extensions of the model might enable testing the effectiveness of visual marketing in dynamic contexts, including TV commercials and the Internet.

In closing, we have estimated the visual salience of brands on the shelf, decomposed it into a component due to the brand's visual image and a component due to consumers' goals and memory, pinpointed the perceptual features that determine brand salience, diagnosed sources of competitive salience and simultaneously estimated their influence on search performance. Further developments could be directed at the analysis of attention to predefined regions of interest in visual marketing stimuli, including text, logo's, and pictorials in print ads and web-pages (Pieters and Wedel 2004; Wedel and Pieters 2000), and whether their attention capture is moderated by consumer factors, such as brand familiarity and product involvement, or task specific factors, such as time pressure and the number of distractors in the display. Extending the present analysis of the visual image to other image content such as shapes (Wolfe and Horowitz 2004), objects (Vogel et al. 2001), or the gist of the image (Oliva and Torralba 2001) are routes for future research into the role of salience in brand search that we intend to pursue.

Chapter 4

Memory Effects in Repeated Brand Search

4.1 Introduction

Consumers visit on average 2.2 supermarkets per week (FMI 2005), in which they are overwhelmed with thousands of packages fighting for attention. When lucky, some of these packages receive a fraction of a consumers' attention in which they need to communicate their identity. This short moment of attention is therefore frequently called "the last salesman", "five-second commercial", or "permanent media" (Keller 2003; Kotler 2003). Peter Gold, vice president Consumer Packaged Goods at Harris Interactive, states that "It is surprising that respondents have the ability to remember and find targets among shelf clutter when the exposure times are less than one second." (Weston 2004). Such statements suggest that packages that are unintentionally attended during a shopping trip may be remembered. For example, when searching today for Miller beer, a consumer may attend and reject several other beer brands, such as Bud or Coors. In a future shopping occasion however, when having decided to buy Bud, this consumer might benefit from the unintentionally acquired information about the package of Bud during the previous shopping occasion. If this unintentionally acquired information affects search, it is an example of incidental learning. Although potentially important there is, as far as we know, no research in marketing that investigates these incidental learning effects of packaging in an everyday shopping situation, such as simply finding a brand on the shelf, and the aim of this research is to study this.

On the other hand, there is much research in marketing on what consumers learn from advertising and its effects on brand memory (Rossiter and Percy 1997; Wedel and Pieters 2000). Although research typically finds that attention to advertisements increases brand memory, it is not obvious whether this generalizes to attention to packages. The reason for this is that besides the different processing goals that are activated when attending to packages in comparison to ads, advertising research shows that memory for ads decreases when consumers are confronted with several ads from the same product category (Burke and Srull 1988; Keller 1991), which may typically also happen when consumers attend to packages on a retail shelf.

Memory effects during visual search tasks, of which locating products on a retail shelf is a special case, is extensively studied in cognitive psychology (Chun and Jiang 1999; Horowitz and Wolfe 2003; Shore and Klein 2000; Williams, Henderson, and Zacks 2005). Many of these studies conclude that learning and memory play an important role during visual search. However, there is still discussion about this topic which is reflected in the ‘amnesic search’ model of Horowitz and Wolfe (2003), which states that visual search does not use memory for previously attended items. Further, most of the positive effects of incidental learning on visual search were obtained in visual search experiments with very simple stimuli, such as colored squares, circles, and single letters. It is not obvious how these results generalize to realistic stimuli, such as packages on a retail shelf. For example, while Williams et al. (2005) find strong long-term memory effects for objects in a realistic visual search display, Lleras and Mühlenen (2004) find that memory effects are reduced when respondents use an active search strategy, which is likely to occur in more difficult visual search situations such as products on retail shelves (see Chapter 3). Moreover, although consumers may have memory for the products on retail shelves due to pre-exposure in earlier shopping trips, it is not obvious whether consumers use this information to adapt their search strategies (Oliva, Wolfe, and Arsenio 2004).

Chapters 2 and 3 modeled the visual search strategies of consumers by analyzing their eye-movements while these consumers tried to find a specific brand on a retail shelf. We found two latent states: localization and identification that guide attention during the search task. In both attention states memory plays an important role. First, in the localization state, consumers use memory to bias the visual salience of packages on the shelf. Visual salience of packages, next to systematic strategies, guides the eyes towards promising candidates in the localization state (where packages with a higher salience are attended first, controlling for the systematic strategies). Second, in the identification state, consumers use memory of the target brand and match its representation to a promising candidate brand on the shelf. Since this model explicitly determines the memory component in visual search for packages on a retail shelf, we use it to determine the memory effects when consumers search for a second time on the same shelf. However, since the model in chapter 2 and 3 does not accommodate multiple searches by the same consumer on the same shelf, and further also does not incorporate consumer characteristics, such as product familiarity, gender, and age, we extend it to account for these effects on memory.

In short, the goal of this research is to determine whether and how consumers incidentally learn any package or other specific information when they only try to find a specific product on the shelf, and whether they use this information to improve search performance to locate other products on the same shelf in subsequent occasions. To accomplish this goal, we first summarize the memory effects found in psychological research on visual search in the next section. In the subsequent section 3, we extend the brand search model of chapters 2 and 3, to incorporate the memory effects that emerge from the literature review in section 2. Section 4 describes the eye-movement experiment, during which 102 consumers searched twice on a retail shelf containing twelve existing coffee brands. Section 5 presents the results of the model estimates and describes whether and how memory effects influence brand search. The final section concludes with a summary of the main findings and marketing implications as well as suggestions for future research.

4.2 Memory in Visual Search

Much research in psychology has investigated memory processes during visual search. These studies involve memory for several different processes, such as memory for specific objects in the display (Oliva et al. 2004; Williams et al. 2005) and the spatial layout (Chun and Jiang 1998; Hoffmann and Sebald 2005). Further, these different memory processes are tested using different methods, for example by explicit memorization tasks (Williams et al. 2005), or by observing the improvement in search performance in subsequent search tasks on the same display (Wolfe, Klempen, and Dahlen 2000b). Other studies tested memory within one search task by analyzing re-fixations on previously fixated objects (McCarley, Wang, Kramer, Irwin, and Peterson 2003), or even designed new search tasks, such as dynamic search in which the position of items on the display changes during the search process (Horowitz and Wolfe 1998). Next to these different memory processes and methods, the stimuli in these search tasks vary widely in nature as well. While most studies use simple stimuli consisting of a few basic features, such as colored squares or letters, some studies use realistic real world stimuli, such as telephones and wallets (Williams et al. 2005). Not surprisingly therefore, these studies lead to different conclusions about the role of memory in visual search tasks.

To structure the research on memory effects in visual search, Table 4.1 presents an overview of the various studies in this area. This table divides the manifestations of memory in two broad categories, (1) across-trial memory, and (2) within-trial memory. Within these two broad categories, the table further subdivides the across-trial memory effects in task-, target-, distractor-, location-, and context-specific memory, and trial-to-trial priming. This organization of the literature is based on the review of Shore and Klein (2000), who divided memory processes in visual search into three groups based on the different time scales present in visual search experiments. The first two groups: perceptual learning and trial-to-trial priming belong to our first category, across-trial memory, in Table 4.1. While trial-to-trial priming is a separate subcategory in Table 4.1, following Shore and Klein we divided perceptual learning into task-, target-, distractor-, and context-specific memory. Further, we also added location-specific memory as a subcategory in this review. The third group in the review of Shore and Klein involves within-trial perceptual memory, which corresponds to within-trial memory in Table 4.1. The remaining paragraphs of this section discuss the main findings in the literature.

Table 4.1 *Literature Overview on Memory Effects in Visual Search*

Study	Visual Search Task	Stimuli	Measure(s)	Moderator	Memory Effect
Across-Trial Memory					
Task-specific memory					
Schneider and Shiffrin (1977)	presence[1]	abstract[2]	accuracy, latency		positive
Shiffrin and Schneider (1977)	presence	abstract	accuracy, latency		positive
Fisk and Hodge (1992)	presence	abstract	latency	relation to target category (+)	positive
Target-specific memory					
Ahissar and Hochstein (1997)	presence unique target	abstract	accuracy	similarity target, distractor (-)	positive
Lubow and Kaplan (1997)	presence unique target	abstract	latency	-	positive
Distractor-specific memory					
Lubow and Kaplan (1997)	presence unique target	abstract	latency	-	positive
Flowers and Smith (1998)	presence	abstract	latency	# possible targets (+)	positive
Wolfe, Klempen, and Dahlen (2000b)	repeated search[3]	abstract	latency, slope[4]	-	-
Oliva, Wolfe, Arsenio (2004)	repeated[2] + panoramic search[5]	concrete[1]	slope	-	positive [6]
Castelhano, Henderson (2005)	presence	concrete	memorization task[7]	-	positive
Williams, Henderson, Zacks (2005)	count targets	concrete	memorization task	relation to target (+), fixations (+)	positive

[1] In a target ‘presence’ task, respondents need to report the presence or absence of a specific target.
[2] Abstract stimuli refer to simple non real world stimuli, such as colored circles, triangles, etc. Concrete stimuli refer to realistic real world objects, such as wallets, car keys, and packages
[3] In repeated search participants search several times on the same display for a different target
[4] With slope in visual search tasks, the authors mean the slope of latency vs. the number of items on the display. This is a standard measure of search efficiency.
[5] In panoramic search, a display is repeated but not shown completely (i.e. a part of the display is hidden, forcing memory search).
[6] Respondents were able to use memory when forced, but prefer visual search although this was more inefficient
[7] Only fixated distractors were tested in the memorization task (forced choice task).

Table 4.1 – Continued

Study	Visual Search Task	Stimuli	Measure(s)	Moderator	Memory Effect
Location-specific memory					
Miller (1988)	presence	abstract	latency	-	positive
Hoffmann and Kunde (1999)	identity[8]	abstract	latency	distance from position (-)	positive
Context-specific memory					
Chun and Jiang (1998)	identity	abstract	latency, slopes	-	positive
Chun and Jiang (1999)	location, identity, static, moving	abstract	latency	-	positive
Peterson and Kramer (2001)	presence	abstract	latency, eye movements	abrupt onset (0)	positive
Olson and Chun (2002)	identity	abstract	latency	-	positive
Tseng and Li (2004)	identity	abstract	latency, eye movements		positive
Lleras and Mühlenen (2004)	identity	abstract -	latency	active (no effect) vs passive strategy	positive
Hidalgo-Sotelo, Oliva, and Torralba (2005)	presence	concrete	latency, eye movements	-	positive
Hoffmann and Sebald (2005)	identity	abstract	latency	-	positive
Brockmole and Henderson (2006)	identity	abstract [9]	latency	-	positive
Trial-to-Trial Priming					
Bravo and Nakayama (1992)	identity and presence	abstract	latency	-	positive
Maljkovic and Nakayama (1994)	identity	abstract	latency	-	positive
Müller, Heller, and Ziegler (1995)	presence	abstract	latency	-	positive
Found and Müller (1996)	identity and presence	abstract	latency	-	positive
Maljkovic and Nakayama (1996)	identity	abstract	latency	-	positive
McPeek, Maljkovic, and Nakayama (1999)	fixation[10]	abstract	latency and accuracy	-	positive
Maljkovic and Nakayama (2000)	identity	abstract	latency	-	positive

[8] In these tasks, respondents need to report the identity of the target, for example search for the letter 'T' and report whether this letter is rotated to the left or to the right.
[9] The display contains a real world context, but does not contain real world objects, i.e. letters.
[10] In this visual search task, respondents need to fixate the target item.

Table 4.1 – Continued

Study	Visual Search Task	Stimuli	Measure(s)	Moderator	Memory Effect
Trial-to-Trial Priming (Continued)					
Hillstrom (2000)	identity	abstract	latency	-	positive
Kumada (2001)	presence, identity, number targets	abstract	latency	Response on other dimension (-)	positive
Kristjánsson, Wang, and Nakayama (2002)	presence	abstract	latency	-	positive
Olivers and Humphreys (2003)	identity	abstract	latency	Orientation +, color ++	positive
Wolfe et al. (2003)	presence	abstract	latency	dimension +, feature ++, mixed +++	positive
Huang, Holcombe, and Pashler (2004)	identity	abstract	latency	-	positive [11]
Wolfe et al. (2004)	presence	concrete	latency	SOA target identity cue (-)	positive
Within-Trial Memory					
Watson and Humphreys (1997)	visual marking[12], presence	abstract	slope	-	positive
Horowitz and Wolfe (1998)	dynamic: presence, identity	abstract	slope	presence vs identity (0)	-
Theeuwes, Kramer, and Atchley (1998)	visual marking[9], presence	abstract	slope	-	positive
Gilchrist and Harvey (2000)	presence	abstract	refixations	-	-[13]
Kristjánsson (2000)	dynamic: presence	abstract	slope[3]	set size (+), distractor location (+)	positive
Gibson et al. (2000)	1 vs 2 targets, static vs dynamic	abstract	latency, slope, accuracy	-	positive
Wolfe, Klempen, and Dahlen (2000b)	previewing target[14]	abstract	latency, slope	SOA (0)	-
Gibson and Jiang (2001)	visual marking[9], presence	abstract	slope	salience target in reduced set (-)	positive
Horowitz and Wolfe (2001)	number of targets	abstract	Model fit	-	-
Peterson, Kramer, Wang et al. (2001)	identity	abstract	refixations	-	positive
Woodman, Vogel and Luck (2001)	identity	abstract	slope	load visual working memory (0)	-

[11] This study also shows repetition priming for irrelevant features.
[12] In a visual marking task, participants see first a part of distractors, after that the remaining distractors plus target are presented (so only search on new items is necessary).
[13] Little memory is found due to Inhibition of Return (IOR).
[14] In this task, the target is sometimes shown before the search display (i.e. preview), and sometimes after (when respondents use memory, visual search should be more efficient in the preview condition).

Table 4.1 – Continued

Study	Visual Search Task	Stimuli	Measure(s)	Moderator	Memory Effect
Within-Trial Memory (Continued)					
Horowitz and Wolfe (2003)	dynamic: identity	abstract	slope	presence vs identity (0)	-
McCarley et al. (2003)	gaze contingent[15], identity	abstract	refixations	lag items fixated (+)	positive
Oh and Kim (2004)	presence	abstract	slope	load spatial working memory (+)	positive
Peterson et al. (2004)	gaze contingent, identity	abstract	refixations	lag (+), landmarks (-), background (--)	positive
Takeda (2004)	number of targets	abstract	model fit	-	positive
Woodman and Luck (2004)	identity	abstract	slope	load spatial working memory (+)	positive

[15] In the gaze contingent task the display is changed after every fixation. A respondent can fixate either on a new item, or to an old, already fixated, item.

4.2.1 Across-Trial Memory

Across-trial memory deals with the question what visual details participants remember after performing a visual search task. Frequently, these effects are studied using several repeated search tasks, and the main question is whether people become more efficient, which is an implicit memory test. However, some researchers also tested memory explicitly after the search task. The following six subparagraphs describe the six subcategories of across-trial memory as presented in Table 4.1.

Task-Specific Memory

Task-specific memory refers to memory effects that occur after many repeated exposures to the same or similar visual search tasks. There is strong evidence that task-, and stimulus-specific skills are learned during repetition of the search task. Influential work by Schneider and Shiffrin (Schneider and Shiffrin 1977; Shiffrin and Schneider 1977) shows that, when the identities of target and distractors remain the same across trials (consistent mapping), visual search may become effortless and hence automatic. Fisk and Hodge (1992) show that these effects even remain after a one-year retention interval.

Task-specific memory has important implications for marketing, as loyal consumers buy and use the same product over and over again. Consequently, loyal consumers may find their favorite products automatically, and these products may even pop-out on the retail shelf even when the consumer is not searching for it, as suggested by Alba and Hutchinson (1987). These predictions, to the best of our knowledge, have not been tested empirically. Further, these task-specific memory results in visual search have been observed with simple stimuli (i.e., the studies of Schneider and Shiffrin, and Shiffrin and Schneider use only letters and numbers), it is not obvious whether these strong effects also occur with more complex stimuli, such as packages.

Target-specific memory

It seems trivial that participants do have target-specific memory after a visual search task, since the response (present vs. absent) requires selective processing of the target. Indeed, in search for an unique target among a set of homogeneous distractors, Lubow and Kaplan (1997) find that search times decrease when the target is used as distractor in an subsequent search task. Further, Ahissar and Hochstein (1997) find that this effect is negatively moderated by task difficulty, i.e. when the target becomes more similar to distractors (Duncan and Humphreys 1992). Note that in these two studies, the target is an odd item, and hence the identity of the target is not important. In natural visual search tasks, such as searching a specific brand on the shelf, the identity of the target is defined and stored in memory. Hence, consumers should have specific memory of the target brand. It is however not clear whether consumers use this information to suppress the old target brand when they later search for another brand on the same shelf.

Distractor-specific memory

During a visual search task, participants usually attend and reject many distractors before finding the target. Tipper (1985) shows that when an object is ignored during a task, this object is inhibited in a subsequent task leading to a slower identification of the ignored object. This phenomenon is called negative priming or latent inhibition (Lubow and Kaplan 1997). Lubow and Kaplan (1997) show that in specific situations this phenomenon might improve search performance, i.e. when participants search repeatedly for an odd target among a same set of homogeneous distractors. Since the repeated distractors are inhibited, the target becomes more salient and hence is located more efficiently. However, this is a very specific search situation, and it is not clear whether participants will benefit from attending rejected distractors, when these distractors later become targets. Not surprisingly therefore, results on distractor-specific memory are mixed.

Wolfe, Klempen, and Dahlen (2000b) do not find support for distractor-specific memory. In a repeated search task, where participants searched on the same display several times for different items, these researchers do not find any change in search performance. Later, Oliva, Wolfe, and Arsenio (2004) find that participants are able to use distractor-specific memory when forced. However, participants seem to ignore this information during normal repeated search tasks, although doing so is inefficient. On the other hand, Castelhano and Henderson (2005) and Williams et al. (2005) find evidence for distractor-specific memory. By analyzing the eye-movements of participants during visual search on realistic stimuli, they find that participants have explicit memory for rejected distractors once the distractor is fixated.

However, their results show that memory is far from perfect with hit rates of about 60% in a forced-choice task.

Location-specific memory

Location-specific memory in visual search has not extensively studied in the psychological literature. This is underlined by the fact that location-specific memory is not mentioned in the overview of Shore and Klein (2000). However, research shows that when in repeated search tasks the target appears more frequently than expected in certain locations, search performance increases when the target appears in high probability locations, and decreases when the target appears in a low probability location (Hoffmann and Kunde 1999; Miller 1988). In marketing, location-specific memory plays an important role as shelf layouts are not at random. For example, premium brands are usually at eye-level, while large-size packages are usually on the bottom of the shelf.

Context-specific memory

Context-specific memory in visual search is an extensively studied phenomenon that manifests implicitly, i.e. without the participants' conscious awareness. This type of memory was first reported in studies by Chun and Jiang (1998), which showed that search performance increases when the context in which a target occurs is repeated. This robust finding is also observed in search through moving objects (Chun and Jiang 1999), and in context consisting of real world scenes (Brockmole and Henderson 2006; Hidalgo-Sotelo et al. 2005). While several studies relied on correlations between target and global context, Olson and Chun (2002) observe context-specific memory as well for local contexts (see also Hoffmann and Sebald 2005).

The effects of context-specific memory in search for specific products on a retail shelf may have important implications for shelf management. When specific products are always located next to each other, for example tooth paste and tooth brushes, reorganizing these products might severely impair findability of products. However, it is not clear whether these effects also generalize to these marketing settings, in view of Lleras and Mühlenen (2004) findings that active search strategies may override the context-specific memory effect. In more complex search tasks, such as locating a product on a retail shelf, consumers usually use top-down active search strategies (see Chapter 3).

Trial-to-trial priming

Trial-to-trial priming refers to the fact that when the target identity remains the same from trial to trial search performance increases compared to when its identity changes (Maljkovic and Nakayama 1994; 2000; Wolfe et al. 2004). This robust finding is strongest for the attention guiding feature, i.e. the feature that is used to locate the target brand (Hillstrom 2000; Huang et al. 2004; Maljkovic and Nakayama 1994). Furthermore, this phenomenon has also been observed in repetition of the target dimension, i.e. the target defining feature is color, or shape across trials (Found and Müller 1996; Müller et al. 1995; Olivers and Humphreys 2003), repetition of the target position (Maljkovic and Nakayama 1996), and for realistic real world stimuli (Wolfe et al. 2004). Trial-to-trial priming suggests that when consumers actively use a specific feature to locate a specific brand, for example the color red for ketchup, they have a tendency to automatically use this feature in next search tasks, even when this feature might not be the most efficient one. However, a recent study of Wolfe et al. (2004) shows that participants can quickly change the guiding feature once they know the properties of the new target. Therefore it is not obvious whether this phenomenon is observed when consumers repeatedly search for a different product on the same retail shelf.

4.2.2 Within-trial memory

Within-trial memory corresponds to the memory effects that are acquired and used within one visual search task. Excluding trivial visual search tasks such as locating a red circle on a black screen, visual search requires a serial inspection of candidate targets on the search display (Treisman and Gelade 1980; Wolfe 1994). Most traditional visual search models in psychology implicitly assume that within-trial memory operates in such a way that previously attended and rejected candidates are not revisited (Horowitz and Wolfe 1998; Kristjánsson 2000). However, this assumption has been challenged by an influential study of Horowitz and Wolfe (1998). Their research shows that search efficiency is not affected when all items in the search display are relocated to another position at a frame rate of about 10 Hz (called dynamic search), compared to a normal visual search task (or static search). Since in a static display tagging of attended items should improve search efficiency compared to a dynamic display, the researchers concluded that visual search is not affected by within-trial memory. However, using a similar dynamic search paradigm, Kristjánsson (2000) found clear differences in search performance by increasing the number of items in the display, and by relocating items only to previously occupied locations. As a response to this research, Horowitz and Wolfe (2003) showed that the decrease in search efficiency in this dynamic condition was due to a too high frame rate that impaired target recognition. Although other studies using different paradigms, such as visual marking (Gibson and Jiang 2001; Theeuwes et al. 1998; Watson and Humphreys 1997), occupied working memory during search (Oh and Kim 2004; Woodman and Luck 2004; Woodman et al. 2001), and analyzing re-fixations (McCarley et al. 2003; Peterson et al. 2004; Peterson et al. 2001) usually report evidence for within-trial memory, there are still conflicting results, as illustrated in Table 4.1.

As summarized by Table 4.1, surprisingly no single study that addresses within-trial memory uses realistic real world objects. There are several reasons that make it likely that when searching for brands on a shelf consumers have and use memory to avoid revisiting previously inspected brands. First it is much easier to store the identity of a brand through semantic information, like its name, than abstract items based on perceptual features. Second, identifying simple objects is very fast compared to brands on a shelf, and therefore the penalty of re-inspecting a brand is much higher, which stimulates consumers to use memory. Third, as noted by Horowitz and Wolfe (2003), in real life consumers might use systematic search strategies, which require memory, to prevent re-visiting previously inspected brands. Next to these arguments, re-inspecting brands in a search task does not necessarily mean that consumers do not remember the re-inspected brands, since consumers might use this strategy to identify the target by means of comparison, i.e. in case when brands are perceptually similar due to for example line extensions, and product imitations (Pieters and Warlop 1999).

In sum, although there is no consensus on how and under which conditions memory processes affect visual search, our overview indicates that most studies find evidence that visual search acquires and uses several forms of memory. As indicated in this review, these processes can be categorized as across-trial memory and within-trial memory. It is not clear however, to which extent these different memory processes affect subsequent search trials, and which types are more important when these effects occur simultaneously. Further, most of these results are obtained using very simple stimuli and many repeated search trials, and it is not straightforward that these results generalize after one or a few search trials to a subsequent search for products on a retail shelf. In the next section we present a model that is able to address these different memory effects when consumers search twice for a (different) product on a retail shelf. The model builds on the brand search model of Chapter 3 that describes the eye-movements of consumers while they are trying to find a predefined target brand.

4.3 Model Formulation

This section extends the brand search model of Chapter 3 so that it incorporates the across-trial memory effects as described in the previous section. In the first paragraph of this section we summarize the foundations of this model. The second paragraph describes how this model is extended to allow repeated searches of one consumer on the same shelf, and to disentangle the different memory effects as described in the previous section. Further this paragraph also extends the model to control for consumer characteristics.

4.3.1 Brand search and the brand search model

When consumers search for a brand on the shelf, consumers need to reduce two types of uncertainties: spatial uncertainty (where candidate target brands are located), and identity uncertainty (what candidate brands are, i.e. target or distractor). To reduce these two uncertainties, attention switches between two latent states, respectively the localization and identification state.

In the localization state, systematic and salience-based strategies guide attention to candidate target brands. Systematic strategies depend on the layout of the shelf (Ponsoda et al. 1995). Since many displays, such as retail shelves are usually horizontally oriented, a horizontal zigzag strategy is frequently observed (Monk 1984). Consumers use these systematic strategies to avoid re-inspecting previously attended candidates, and hence compensate for a limited within-trial memory (Horowitz and Wolfe 2003). Salience-based strategies direct visual attention to conspicuous locations on the shelf. For example a bright package is eye-catching among dark packages, and hence might attract attention. The salience map is constructed in the consumers' brain immediately after it is exposed to a retail shelf (Itti and Koch 2001; Koch and Ullman 1985; Treue 2003; Wolfe 1994), and arises from bottom-up and top-down weighting of basic perceptual features, such as color, luminance, and edges. The bottom-up, or stimulus based component depends purely on the objects on the shelf (i.e. an eye-catching promotional tag, or a bright package among dark packages). The top-down, or memory-based component modulates these bottom-up weights based on knowledge and goals of the consumer. For example, when searching for Coca Cola a consumer might give higher weight to the color red, while searching for PepsiCo might increase the weight on blue. Since top-down weights are memory-based, the memory effects presented in the previous section affect the salience map via these top-down weights (Wolfe et al. 2003).

In the identification state, attention is redirected to the same brand in order to determine whether the selected brand is a target or distractor brand. In this state, the visual brain gathers relevant information about the candidate, such as its name, logo, package shape, and text, which is compared to a memory representation of the target in the consumers' mind (Duncan and Humphreys 1989). The efficiency of this process depends on whether the consumer is able to select diagnostic information, and on the quality of the memory representation. For example, a consumer determining whether a selected candidate is M&M's Crispy or another flavor, might have to read information on the package. However, when the consumer has an accurate memory representation of the blue Crispy package, a color check might already determine its identity. Therefore, since performance in the identification state is memory-based through the memory-representation, previous exposure to the target brand might improve search performance.

In sum, the brand search model incorporates memory effects through, 1) systematic search strategies, 2) top-down modulation of the salience map, and 3) through the memory representation of the target brand, which is used to determine whether a candidate is a target or a distractor in the identification state. The consequences of within-trial memory are therefore already incorporated in the brand search model via the systematic strategies. However, since the current model version does not allow repeated search, across-trial memory is not incorporated. Because brand search is affected by three memory components, the across-trial memory effects may affect the search process through one of these three components. The next section extends these three memory components to include across-trial memory effects.

4.3.2 A model for repeated brand search

As described in the previous section, memory effects appear in three components in the brand search model. First, these effects are incorporated by the weights of the systematic search strategies ω_{cts}^{g} [1], with $c = 1,..,C$ representing the set of consumers, $t = 1,..,T$ indicating the number of repeated search tasks (hence $T = 2$), $s = 1,..,S$ representing the set of systematic search strategies (in the empirical example we use $S = 2$, i.e. horizontal left-right, and right-left), and $g = 1,..,G$ representing the set of possible target brands (in the empirical example $G = 2$, corresponding to Van Nelle and Douwe Egberts). Second, memory effects affect the weight of the perceptual features ψ_{ctm}^{g} [2], with $m = 1,..,M$ representing the set of basic features (in the empirical example $M = 4$, i.e. luminance and the colors red, gold, and blue). Finally, memory plays a role in the identification state through matching the attended brands with a memory representation of the target. We incorporate this effect by including the number of repetition fixations on the target ζ_{ct}^{g} [3], as memory for the target suggests faster identification and hence less re-fixations on the target in the identification state. These three memory components for each consumer *c* in each task *t* for each target *g*

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[1] Note, for readability we changed the notation compared to Chapter 3. ω_{cts}^{g} corresponds to $\theta_{j=1,ck}, k \in K_s$ in Chapter 3 where K_s corresponds to the set of systematic search strategies.

[2] ψ_{cts}^{g} corresponds to $\theta_{j=1,ck}, k \in K_m$ in the original notation of the brand search model, where K_m refers to the set of basic features.

[3] $\zeta_{ct}^{g} = \sum_{i=1}^{n_{ct}} \left(I\left\{z_{cti} = 2\right\} \cdot S_c^D\left(a_{cti}, b_{cti}, g\right)\right)$, where n_{ct} corresponds to the number of fixations of consumer *c* in task *t*, $I\left\{z_{cti} = 2\right\}$ is the indicator function that equals 1 when $z_{cti} = 2$, zero otherwise. z_{cti} indicates the state of fixation *i* of consumer *c* in task *t* (state 2 corresponds to the identification state), and $S_c^D\left(a_{cti}, b_{cti}, g\right)$ indicates whether the fixated pixel, with coordinates $\left(a_{cti}, b_{cti}\right)$ is on the target brand *g*. $\left(a_{cti}, b_{cti}\right)$ corresponds to the coordinates of the position of fixation *i* of consumer *c* in task *t*. Note that due to smoothing of $S_c^D\left(a_{cti}, b_{cti}, g\right)$ to allow a perceptual field of 2 degrees, ζ_{ct}^{g} is a positively continuous variable.

can be stacked in the vector $\upsilon_{ct}^{g} = \left[\omega_{ct}^{g} \quad \psi_{ct}^{g} \quad \zeta_{ct}^{g}\right]'$ with size $(S+M+1)\times 1$. Similar as in the previous two chapters, we assume that these effects are drawn from a normal distribution with mean vector $\upsilon_{0}^{g} = \left[\omega_{0}^{g} \quad \psi_{0}^{g} \quad \zeta_{0}^{g}\right]'$ and diagonal covariance matrix Σ to allow for heterogeneity across consumers. An extension compared to the previous chapters is that in this formulation the mean-vector υ_{ct}^{g} may depend on individual consumer characteristics. Note that in the original brand search model the overall mean υ_{0}^{g} equals $\left[\mu_{S} \quad \mu_{M}+\tau_{M}^{g} \quad \zeta_{ct}^{g}\right]$ and $\Sigma_{(S+M+1),(S+M+1)} = 0$. With other words, the overall mean μ_{S} of the systematic strategy was equal for each consumer independent of the target. The mean of the feature weights $\mu_{M}+\tau_{M}^{g}$ differed between search targets through the task dependent top-down (memory-based) weight τ_{M}^{g}. In the next paragraph we show how we incorporate consumer specific effects in the mean vector υ_{0}^{g}, to uncover memory effects.

Modeling across-trial memory effects

Since the original brand search model already incorporates within-trial memory effects through the systematic strategies, equation (1) extends υ_{ct}^{g} to incorporate across-trial memory effects.

$$\upsilon_{ct}^{g} = \upsilon_{0}^{g} + \upsilon_{1}^{g}\cdot TASK_{ct} + \upsilon_{2}^{g}\cdot TARGET_{ct} + \upsilon_{3}^{g}\cdot DISTRACTOR_{ct} + \upsilon_{4}\cdot PRIMING_{ct} + \varepsilon_{ct}^{g} \quad (1)$$

In equation (1), the $(S+M+1)\times 1$ parameter vectors υ_{h}^{g}, $h = 0,..,3$, and the $(S+M+1)\times(S+M+1)$ parameter matrix υ_{4} indicate the across-trial effects on the different top-down components in the repeated brand search model. Further, ε_{ct}^{g} is a disturbance term, which follows a normal distribution. In this equation, the variables $TASK_{ct}$, $TARGET_{ct}$, $DISTRACTOR_{ct}$, and the $(S+M+1)\times 1$-vector $PRIMING_{ct}$ represent task-, target-, distractor-specific memory and trial-to-trial priming respectively. Note, υ_{ct}^{g} is not affected by location-, and context-specific memory, because these effects do not affect the three components of υ_{ct}^{g}. Results of Tseng and Li (2004) using simple stimuli show that context-specific memory only affects the period prior to fixating the target, which correspond to the localization state. When consumers have location- and context-specific memory, they remember the location of a specific brand rather than the features in that location. Therefore, the remembered location receives a higher probability of being attended independent of its features. To incorporate context- and location-specific memory the vector υ_{ct}^{g} should be extended with two components corresponding to these two memory effects respectively. These variables can be coded in a similar way as features, but instead of coding pixels with a specific feature as one, pixels in a specific location receive a value of 1 and zeros otherwise. However, since the shelf in our empirical example is not fixed, we cannot disentangle location- and context-specific effects, and we therefore do not incorporate these effects here.

As indicated in equation (1), *task-specific memory* is modeled through the dummy variable $TASK_{ct}$ that equals 1 when $t = 2$ and zero otherwise. *Target-specific memory* is incorporated by the variable $TARGET_{ct}$, which equals $\sum_{i=1}^{n_{c,t-1}} S_c^D\left(a_{c,t-1,i}, b_{c,t-1,i}, g_{c,t-1}\right)$ when $t = 2$ and zero otherwise. In this formula, $S_c^D\left(a,b,g\right)$ represents the value of brand *g* in pixel location $\left(a,b\right)$, and $\left(a_{c,t-1,i}, b_{c,t-1,i}\right)$ represents the coordinates of fixation *i* of consumer *c* in task *t*, and where $g_{c,t-1}$ indicates the target of consumer *c* in task $t-1$. The variable $TARGET_{ct}$ measures target-specific memory as the number of fixations (weighted by the smoothed surface of brand $g_{c,t-1}$) in task 1 on the target of task 1, which can be interpreted as how consumer information consumer *c* acquired of the target in task 1. This is in line with the results of Castelhano and Henderson (2005) and Williams et al. (2005) who show that participants only have memory for objects in a visual search task when they previously fixated these objects. We also account for *distractor-specific memory* for brand g_{c2}, i.e. a distractor brand in task 1 that becomes target in task 2. We do not take into account distractor specific memory of the remaining brands, since it is unlikely that a consumer uses this knowledge to locate brand *g* in task 2 (Wolfe et al. 2003). Distractor-specific memory is modeled similarly as target-specific memory through the variable $DISTRACTOR_{ct}$, which is represented as the number of eye-fixations in task 1 on the target of task 2, and hence represents the amount of information extracted from this packages brand. For $t = 2$ this variable corresponds to the number of weighted fixations of consumer *c* in task 1 on brand g_{c2}, which equals $\sum_{i=1}^{n_{c,t-1}} S_c^D\left(a_{c,t-1,i}, b_{c,t-1,i}, g_{ct}\right)$, for $t=2$, and zero otherwise. Finally, *trial-to-trial priming* effects are incorporated by the variable $PRIMING_{ct}$. Since trial-to-trial priming suggests that when a specific feature receives a high weight in search task 1, it will receive a relatively higher weight in task 2 as well. Therefore the mean of feature *m* for consumer *c* in task 2 depends on the weight of that feature in task 1. Although trial-to-trial priming has not been reported and studied for systematic search strategies, we include these effects for systematic search as well. We model the variable $PRIMING_{ct}$ for $t>1$ as the following $(S+M+1)\times 1$ -vector: $\left[\omega^g_{c,t-1,1} .. \omega^g_{c,t-1,S} \quad \psi^g_{c,t-1,1} .. \psi^g_{c,t-1,M} \quad 0\right]'$ and $\mathbf{0}$ for $t=1$. Because $PRIMING_{ct}$ is a vector, υ_4 is a $(S+M+1)\times(S+M+1)$-matrix. Although cross effects within one dimension (i.e. color, orientation etc.) may occur, these effects are usually weaker (Found and Müller 1996; Wolfe et al. 2003), therefore we do not take these effects into account and hence υ_4 is diagonal. The last element in the $PRIMING_{ct}$ vector equals zero, since priming effects occur on the weights in the localization state, and not on repetition on the target in the identification state.

Consumer characteristics

Top-down strategies may differ between consumers, based on knowledge of the product or category. We therefore include consumer characteristics into the model in a similar way as the across-trial memory effects in equation (1). In this research we include gender, age, and product familiarity as control variables in equation (1).

In sum, the proposed model allows for repeated brand searches of the same consumer, and incorporates consumer characteristics that may influence search strategy, and can establish if and more importantly how memory affects search processes and performance. Although the presented repeated search model assumes that the shelf is the same within consumers, i.e. S_c^D does not depend on the task, this can be easily expanded by making S_c^D task dependent. Relocating products on the shelf in different search tasks is necessary to disentangle location- and context-specific memory.

Similar to the brand search model (chapters 2 and 3), the model is estimated using a MCMC algorithm with auxiliary variables (Rossi and Allenby 2003: see Appendix for the algorithm). Model estimation is based on 25,000 draws, thinned 1 in 10, with a burn-in of 25,000 iterations.

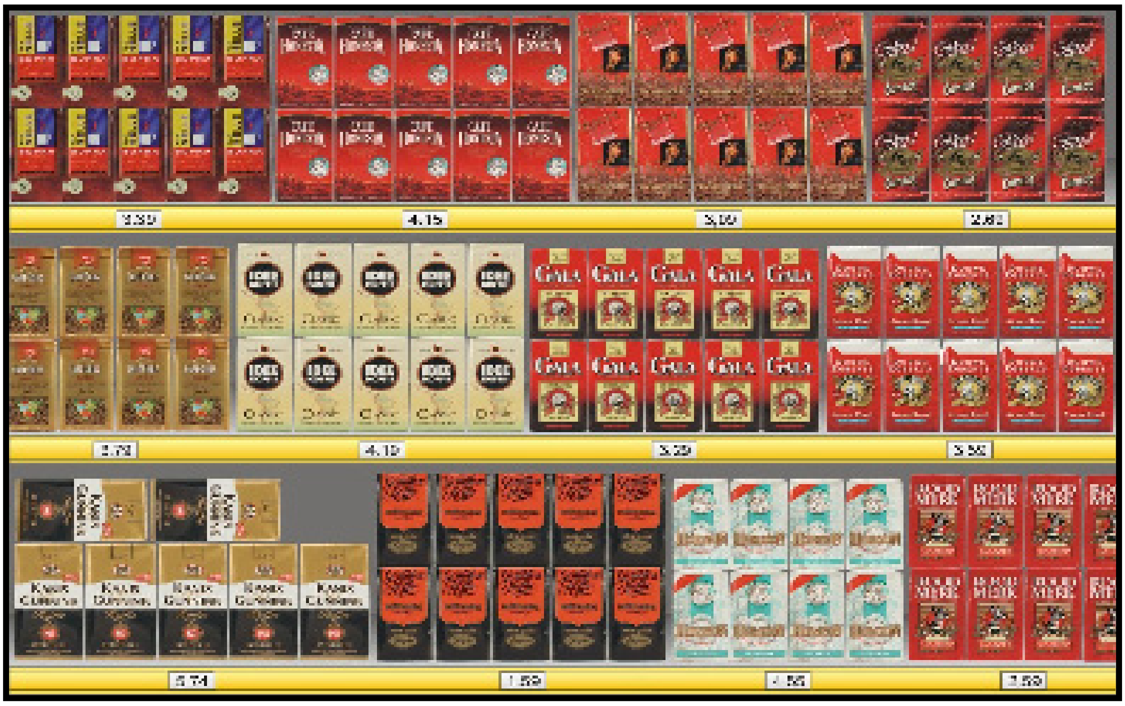
4.4 Repeated Brand Search Experiment

A commercial marketing research company collected the data of 102 randomly selected consumers (56 males and females between 16 and 55 years of age) who searched twice for a different brand of coffee on a computer-simulated retail shelf (see Figure 4.1)[4], which allows us to investigate incidental learning effects, reflected in across-trial memory. The shelf, presented on a 21-inch search display (1,024 x 1,280 pixels), contained 12 different existing national coffee brands, and each consumer searched once for Van Nelle (VN), and once for Douwe Egberts (DE). The order of these brands was randomly assigned to consumers, 40 consumers first searched for DE and than for VN, while the remaining 62 consumers first searched for VN and than for DE.

Before each search task the consumers were instructed to find an indicated target brand, and they were told that they had sufficient time to locate the brand. After the instruction, the consumers were exposed to the shelf (Figure 4.1) on which they had to locate the target brand. When a consumer located the target brand, (s)he had to indicate its location by pointing at the touch-sensitive screen, after which search performance was recorded as search time and accuracy (stored as dummy variable which equaled one when the pointed location was correct, and zero otherwise). When a consumer did not indicate a brand within 10 seconds, a period that is representative for search for fast moving consumer goods (Hoyer 1984; Leong 1993), the search task was terminated, and accuracy was set to zero and search time to 10 seconds. During the repeated brand search task, the eye-movements of consumers were recorded by infrared corneal eye-tracking equipment with a sampling rate of 50 Hz and spatial resolution of 0.5° (Duchowski 2003). This measurement was unobtrusive and consumers could freely move their head within a virtual box of 19 inches.

[4] This dataset is similar to the dataset in chapter 2, however it incorporates a different set of consumers.

Figure 4.1 *The Computer-Mediated Retail Shelf*



Note: The shelf contains 12 different coffee brands. Van Nelle is located at the top-left of the shelf, and Douwe Egberts is located at the right of the middle shelf.

Besides other unrelated tasks in the experiment, all consumers filled in a questionnaire containing demographic and product-related questions. In the questionnaire, 39 consumers indicated that they usually drink DE, and 11 consumers indicated to drink VN. These answers were used to code the dummy control variable $BRAND\_FAMILIARITY_{ct}$ that received the value one when the target of consumer c in task t corresponded to his favorite brand. Next to these descriptive variables, the picture of the shelf was transformed into a $A \cdot B \times M$ -matrix S^M containing for each pixel $(a,b) \in A \times B$ (in this application $A = 834$, and $B = 1{,}157$) a value for three color features red, gold, and blue, and for the feature luminance (hence $M = 4$ basic features). These features are chosen since these are the most important colors in this category, and these three colors alone represent more than 50% of the coffee category. Further, the explanatory $A \cdot B \times D$ matrix S^D represents for each of the $D = 12$ brands whether a certain pixel $(a,b) \in A \times B$ is on the surface of brand $d \in D$. Similar as in Chapter 2, we smooth S^M and S^D by a normal kernel with standard deviation equal to 2 degrees of visual angle, to account for the perceptual field around an eye-fixation point.

4.5 Results

4.5.1 Descriptive Results

Table 4.2 presents descriptive results of the 102 consumers in the repeated brand search experiment. The results are divided by target brand, i.e. DE and VN, and further by first and second trial. In total, the data set contains 3,412 eye-fixations spread over the 102 repeated search trials. As can be concluded from both search performance measures, search time and accuracy, search performance is better for DE than for VN (mean search time DE = 3.34 sec., VN = 5.26 sec., paired t-test: $t = 6.25$, $p < 0.01$, and percentage correct DE = 87%, VN = 75%, McMenar test for paired difference $p =< 0.01$). This result is not surprising, since DE is the market leader which is also reflected in our sample by a higher preference for DE. More surprisingly is the difference in search performance for trial 1 vs. trial 2. Although for VN search performance improves (mean search time trial 1 = 5.64, trial 2 = 4.68, $t = 1.90$, $p = 0.06$, percentage correct trial 1 = 66%, trial 2 = 90% , $z = 2.75$, $p < 0.01$), for DE search performance decreases in the second trial, especially accuracy (mean search time trial 1 = 3.16, trial 2 = 3.45, $t = 0.75$, $p = 0.46$, percentage correct trial 1 = 100%, trial 2 = 79% , $z = 3.10$, $p < 0.01$). This decrease in search accuracy suggests that consumers in the second trial put less effort in identifying the target brand, as none of these consumers is out of time. However, these effects do not indicate whether consumers used any information of the first trial in the second trial, since different search strategies and consumer characteristics may lead to similar search performances and vice a versa (Pashler 1998; Sanders and Donk 1996; Wolfe 1998). Whether consumers use any memory in the second trial acquired by the first one is discussed in section 5.4.

Table 4.2 *Descriptive Statistics*

		Target Brands by Trial					
		Douwe Egberts (DE)			Van Nelle (VN)		
	Overall	Overall	Trial 1	Trial 2	Overall	Trial 1	Trail 2
N consumers	102	102	40	62	102	62	40
N fixations	3,412	1,360	509	851	2,052	1,339	713
Search:							
Time, *M* sec.	4.30	3.34	3.16	3.45	5.26	5.64	4.68
(*SD*)	(2.46)	(1.96)	(1.81)	(2.06)	(2.53)	(2.77)	(2.01)
Accurate	81%	87%	100%	79%	75%	66%	90%
Out of time	5%	0%	0%	0%	11%	18%	0%
Inaccurate	13%	13%	0%	21%	14%	16%	10%
Features:							
% Red	31%	55%			27%		
% Gold	25%	13%			14%		
% Blue	0.5%	0.7%			4.1%		
M Luminance	0.46	0.49			0.38		

Note: Colors are coded as dummy variables. Luminance is normalized between zero and one, with higher values corresponding to higher luminance.

4.5.2 Brand search for Douwe Egberts and Van Nelle

Tables 4.3 and 4.4 present the basic search process parameters (see Chapters 2 and 3). As indicated by the attention switching matrix in Table 4.3, consumers switch frequently between the localization and identification state, confirming results of previous brand search tasks. Consumers spend on average longer in the localization state (posterior median: 60%) than in the identification state (posterior median: 40%, with all posterior draws smaller than 50%). The reason for this is mainly due to the fact that consumers seem to identify brands relatively fast, as suggested by the lower tendency to stay in the identification state (posterior median: 33%) as opposed to switch to this state from the localization state (posterior median: 46%, with all posterior draws higher than staying in the identification state).

Table 4.3 *Attention Switching During Target Search: Median and 95% Credible Intervals of Transition Probabilities*

	Destination State:					
	Localization			Identification		
Source State:	0.025	0.500	0.975	0.025	0.500	0.975
Localization	0.51	0.54	0.57	0.43	0.46	0.49
Identification	0.64	0.67	0.72	0.28	0.33	0.36
Limiting probabilities	0.58	0.60	0.62	0.38	0.40	0.42

Note: The limiting probability for the localization state is computed as: $\frac{1-p_{22}}{1+p_{12}-p_{22}}$, and for the identification state as: $1-\frac{1-p_{22}}{1+p_{12}-p_{22}}$ (see Ross (1997), p. 174).

Table 4.4 presents the parameter estimates υ_0^g of the average attention guidance in the localization state for both target brands (computed as the sum of the bottom-up and top-down weights), and the number of identification fixations on the target. This table shows that the color red, the category code for coffee, is most important in shaping the salience map for DE, the market leader (posterior median for DE: 0.60, and all posterior draws positive). This color also positively influences the salience map when VN is the target brand, although clearly less strong (posterior median: 0.08, and 93% of the posterior draws positive). Next to the color red, blue has the highest positive weight in the salience map when VN is the target (posterior median: 0.29, all posterior draws positive), while it is supressed in the salience map of DE (posterior median: -0.30, all posterior draws negative). Further, all 95% posterior intervals of the other two features, the color gold and luminance, contain zero, except for the market leader DE which is also guided to brighter locations (posterior median of luminance for DE: 0.20, all posterior draws positive). Next to the salience map, the two systematic search strategies are also important in guiding attention in the localization state (posterior medians for DE : 0.30 and 0.26, medians VN: 0.40 and 0.36 for left-right, and right-left zigzag strategies respectively, all posterior draws

Table 4.4 *Attention Guidance for both targets DE and VN: Median and 95% Credible Intervals*

Parameter	Mean DE			Mean VN			St. dev.
	0.025	0.500	0.975	0.025	0.500	0.975	median
Localization State:							
Salience Search (ω_0)							
1. Color:							
Red	**0.50**	**0.60**	**0.71**	-0.03	0.08	0.20	0.06
Gold	-0.28	-0.13	0.01	-0.07	0.05	0.17	0.07
Blue	**-0.40**	**-0.30**	**-0.16**	**0.23**	**0.29**	**0.34**	0.08
2. Luminance:	**0.10**	**0.20**	**0.30**	-0.15	-0.05	0.04	0.08
Systematic Search (ψ_0)							
Horizontal zigzag:							
Left-right	**0.17**	**0.30**	**0.42**	**0.31**	**0.40**	**0.48**	0.08
Right-left	**0.15**	**0.26**	**0.36**	**0.28**	**0.36**	**0.44**	0.06
Identification State:							
Identification target (ζ_0)	**1.11**	**1.52**	**1.94**	**0.59**	**1.04**	**1.49**	-[1]

Note: **Bold** credible intervals for the means do not cover zero.

[1] The standard deviation of the regression on the number of identification fixations on the target is task specific. The posterior median of the standard deviation for DE equals 0.77, and for VN equals 0.97.

positive). For VN both systematic search strategies seem to play a more important role in guiding attention during the localization state (for the left-right strategy 91% of the posterior draws are higher for VN compared to DE, and for right-left 94%). This suggests that consumers have a better knowledge of the package characteristics of DE, the market leader, compared to VN, and hence have more confidence in its salience map. Interestingly however, the number of identification fixations on the target for the market leader DE is higher than for VN (posterior medians: 1.52 for DE, and 1.04 for VN, with 94% of the posterior draws for VN larger than DE). This result suggest that the identity uncertainty of DE is higher than for VN, which is probably due to the fact that the package of DE is harder to distinguish from its competitors than VN.

4.5.3 Search Performance

Table 4.5 presents for both target brands, DE and VN, the relationship of brand salience and the number of identification fixations on the target brand to search performance, which is measured as search time and accuracy. Clearly as expected, brand salience has a negative effect on search time (posterior medians: -0.36, and -0.06 for DE and VN respectively) and a positive effect on accuracy (posterior medians: 6.76, and 1.92 for DE and VN respectively). Further the number of identification fixations on the target slows down brand search (posterior medians: 0.29 for DE, and 0.12 for VN), while it increases search accuracy (posterior medians: 1.29 for DE, and 3.08 for VN).

As described in the previous section, across-trial memory effects may affect the top-down weights on the salience map and it may influence the number of repeated fixations on the target brand. Therefore the results so far show that across-trial effects may indirectly influence search performance via the salience map and the matching representations in the identification state. The across-trial memory effects during repeated search are discussed in the next section.

Table 4.5 *Search Performance: Median and 95% Credible Intervals*

Predictor	Brand Search Performance					
	log (Search Time)			Search Accuracy		
	0.025	0.500	0.975	0.025	0.500	0.975
Target 1: DE						
Constant	**3.14**	**4.73**	**6.80**	**-116.38**	**-70.16**	**-15.45**
Brand salience	**-0.53**	**-0.36**	**-0.22**	**1.37**	**6.76**	**11.91**
Identification on target brand [1]	**0.13**	**0.29**	**0.43**	-2.72	1.29	4.93
Variance	**0.02**	**0.11**	**0.21**	-	1 [2]	-
Target 2: VN						
Constant	**2.16**	**2.60**	**3.23**	**-61.13**	**-35.69**	**-3.61**
Brand salience	**-0.09**	**-0.06**	**-0.04**	**0.17**	**1.92**	**3.10**
Identification on target brand [1]	**0.03**	**0.12**	**0.23**	**0.28**	**3.08**	**7.05**
Variance	**0.02**	**0.13**	**0.19**	-	1 [2]	-

Note: **Bold** credible intervals do not cover zero. [1] Number of identification fixations on SKUs of target brand. [2] Variance of search accuracy set to one for identification.

4.5.4 Across-trial memory effects

While controlling for consumer characteristics, Table 4.6 presents the across-trial memory effects during the repeated search task on the three memory components ω_{ct}^{g}, ψ_{ct}^{g}, and id_{ct}^{g}, respectively systematic search, top-down weights of the salience map, and repeated fixations on the target brand in the identification state. For interpretation, the effects on the top-down weights are translated in effects on target salience[5]. Table 4.6 shows that for both targets, older people are less able to construct and informative salience maps such that the target gets more salient (posterior medians: -0.30 for DE, and -1.09 for VN). This result is in line with research on visual search and age that shows that older people are less efficient in visual search tasks (Ball, Beard, Roenker, Miller, and Griggs 1988; Hommel, Li, and Li 2004). The results show that this salience effect is due to a less effective top-down biasing of the diagnostic feature (i.e. posterior median color red: -0.05 for DE, and -0.02 for blue when VN is the target). Next to an age effect, females seem to rely more on the salience map, resulting in smaller systematic search weights (left-right and right-left posterior medians: -0.12, and 0.05 for DE, and -0.07, and -0.08 for VN respectively). Further, females seem to spend more time on identifying the target, especially for the more difficult target VN (median: 0.78, all but one of the posterior draws positive). Further, brand familiarity has a positive effect on target salience, although this effect is not very strong (posterior median: 0.32 for DE, 97% of posterior draws are positive, and 0.98 for VN with 76% of posterior draws positive), which is probably due to popularity of the coffee category that most consumers know.

As indicated by Table 4.6, *task-specific memory* seem to affect both representation matching, resulting in less repeated fixations on the target brand (posterior medians: -0.57 for DE, and –0.66 for VN, 97% and 90% of the posterior draws are negative respectively), and the salience of the target brand (posterior median: -0,14 for DE, and 5.03 for VN). The negative effects, especially the stronger one for DE, might explain why consumers in the second search trial are relatively inaccurate (see Table 4.2). Although the strong positive effect of task-specific

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[5] We define target salience as the salience of the search target. The effects on target salience is computed by projecting for each posterior draw the independent variables on the target salience (see Appendix step 9).

Table 4.6 *Across-Trial Memory Effects on Attention Guidance*

			Parameter					
			Salience Search				Systematic Search	
Source:	Target Salience[1]	Identification	Red	Gold	Blue	Luminance	Left-right	Right-left
Target 1: DE								
Gender (female=1, male=0)	0.23	0.14	0.07*	0.03	-0.08*	0.02	-0.12**	0.04
Age	-0.30**	0.06	-0.05**	0.01	0.04*	-0.01	0.01	0.01
Familiarity brand	0.32*	0.05	0.04	-0.00	0.01	-0.02	0.03	-0.04
Across-trial memory effects:								
Task-specific	-0.14**	-0.57*	-0.10*	0.32**	0.07	-0.07	0.00	-0.02
Target-specific (VN)	0.17*	0.03	-0.01	-0.04**	0.03**	-0.01	0.00	0.01
Distractor-specific (DE)	0.10**	0.01	-0.00	-0.05*	0.04	-0.01	0.01	-0.00
Target 2: VN								
Gender (female=1, male=0)	1.26	0.78**	0.05	0.06	0.03	-0.01	-0.07	-0.08**
Age	-1.09**	0.05	0.04*	0.03	-0.02*	-0.00	-0.03	-0.02
Familiarity brand	0.98	-0.03	0.08	-0.11	0.00	-0.05	-0.00	-0.04
Across-trial memory effects:								
Task-specific	5.03**	-0.66	-0.08	-0.06	0.11	-0.11	-0.02	0.16
Target-specific (DE)	-1.09**	0.06	0.03	0.03	-0.01	0.02	0.01	-0.04
Distractor-specific (VN)	4.64**	0.09	-0.17**	-0.04	0.06**	-0.01	0.06	0.08
Trial-to-Trial Priming	-	-	0.04	0.03	0.15	-0.02	0.04	-0.02

[1] Parameter estimates for the effect on salience of the target are multiplied by 100.
* 90% confidence interval does not contain zero; ** 95% confidence interval does not contain zero.

memory on target salience for VN is as expected, which contributes also to the fact that none of the consumers is out of time in the second search task (see Table 4.2), the negative effect of DE is somewhat surprising. This effect might be due to the fact that consumers in the first task may have found out that the color red is not such an effective feature since this color is shared by most of the brands on the shelf, leading to a more negative weight of the color red in the second trial (posterior median: -0.10, with 95% of the posterior draws negative).

For both brands, *distractor-specific memory* increases salience of the target brand in the second trial (posterior medians: 0.10 for DE, and 4.64 for VN). This strong result shows that next to remembering fixated distractors (Castelhano and Henderson 2005; Williams et al. 2005), consumers also use this knowledge in subsequent search trials. However, consumers do not rely more on the salience map or spend less resources on identification due to this information, as there are no effect on the systematic search parameters.

As expected consumers do have *target-specific memory*, and this knowledge seems to affect target salience in the second trial (posterior medians: 0.17 for DE, and -1.09 for VN). Similar as with task-specific memory, we find an opposite effect for both brands. This effect might be explained by the fact that consumers, who need to attend more to the market leader DE, probably do not learn much about the category as this brand is highly familiar and relatively similar to other brands. However, consumers gathering more information about the less known and more dissimilar brand in the category, VN, seem to get more useful information that might help them in constructing a more effective salience map.

Although frequently observed within visual search tasks, *trial-to-trial priming* did not occur on any of the features and systematic search strategies in our repeated brand search task. This is not surprising, since before the start of each search trial the target brand was clearly stated to the consumer, and consumers may change top-down weights in a few milliseconds based on this information (Wolfe et al. 2004).

4.6 Discussion and Implications

This research shows that consumers use specific information acquired in a previous brand search trial to find products in a subsequent search trial. This result is fascinating, given the many competitive brands on the shelf, the specific search goal, and the short search duration of about 4 seconds. Our results show that only a few eye-fixations on a specific brand are enough to acquire sufficient information to enhance its salience in a subsequent trial, which underscores the importance of packages as a communication tool.

Further, this research integrates memory effects found in previous studies on visual search, and shows that these effects may work simultaneously during repeated brand search, affecting different memory components of the search process. These effects are not distinguishable by using simple measures of search performance, such as reaction times and accuracy, which is common practice in the psychological literature that studied these effects (see Table 4.1). This emphasizes the importance of eye-tracking research in studying memory effects of visual attention in complex scenes as is the case in a marketing environment. The extended brand search model, allowing for repeated searches, proved to be a useful tool to analyze different memory effects on different components of the search process. While differences in search times and accuracies were not consistent across the two search targets and trials, the effects on the different memory components across targets and trials showed a clearly interpretable pattern. Further, the repeated brand search model shows how these memory effects on search performance are mediated by these memory components in the search process, resulting in a clear explanation of the seemingly inconsistent search performance measures across targets and trials.

4.6.1 Managerial Implications

Previous research in marketing already stressed the importance of attracting attention towards packages on a shelf to increase consideration and hence sales (Drèze et al. 1994; Hoyer 1984). This research shows that catching consumers' attention towards packages is even more important, since a few eye fixations on a brand already affects its salience in subsequent search occasions. This strong effect is even observed when consumers rejected the attended brand, and could at most observe perceptual features of the package, since reading specific package information was not possible due to the nature of the experiment. Therefore, in situations where consumers are able to inspect package information, the observed effect may even be stronger, since package inspection leads to more attention to the brand.

Another important finding of this research is that consumers spend relatively little energy on identifying target brands, which leads to a large proportion of inaccurate responses. Strikingly, our results show that the amount of attention spend on identifying the target in the second trial is even lower for both targets. This suggests that consumers may even become sloppier, and hence make more inaccurate decisions during a shopping trip in for example a supermarket. This consequence is clearly visible in the high number of inaccurate decisions in the second trial, which is especially apparent for the market leader DE. The higher tendency to make identification mistakes for DE compared to VN when spending less effort on identification is not surprising, given the fact that many brands on the shelf look relatively similar to DE compared to VN. Because consumers tend to spend little time on identifying brands, it is important for a manufacturer to design diagnostic packages that can be identified quickly based on a few simple perceptual features.

So far these implications all pertained to across-trial memory effects. However, the higher weights on systematic search for VN compared to DE suggest that consumers also actively use this tactic to increase within-trial memory artificially while searching for VN. This is probably due to the fact that DE is a more familiar brand, and hence consumers trust more its corresponding salience map. Therefore, in relatively unfamiliar categories, or categories where packages are hard to distinguish based on perceptual features, retailers should put more effort in its organization, as these categories are likely to benefit more from specific reallocations than categories where consumers rely more on a salience based strategy.

4.6.2 Implications for Memory Research in Visual Search

Although, as indicated in Table 4.1, much research in cognitive psychology extensively studies memory effects during visual search, the present study has several additional implications. First, while most studies reported in Table 4.1 are mainly interested in one specific memory effect at a time, the present research shows that it is important to account for other memory effects as well, as these effects may work simultaneously. Not controlling for these simultaneous memory effects, may seriously bias results (Kristjánsson et al. 2002). Second, most of the reviewed studies in Table 4.1 use simple visual search displays to uncover specific memory effects and to be able to control for potential other effects. However, based on these studies it is not obvious whether the memory effects also hold in search for a brand on a retail shelf, as illustrated by Wolfe (1998, p.56) ".. will any of the models of visual search survive the confrontation with the real world? You don't get several hundred trials with the same targets and distractors.". The presented results in this paper show that these memory effects do exist in realistic stimuli. Further, as indicated by the seemingly inconsistent search performance measures, speed and accuracy are not reliable measures to uncover these memory effects in real world search tasks, supporting the use of eye movements and memorization techniques to study these effects in real world scenes (Castelhano and Henderson 2005; Hidalgo-Sotelo et al. 2005; Williams et al. 2005). Finally, none of the reviewed studies in Table 4.1 accommodate for individual differences. This research shows that individual differences may have a substantial influence on the search process.

4.6.3 Limitations and Future Research Avenues

The present results are found in a relatively familiar product category, as shown by the high search performance and the effective top-down weights of consumers. It would be interesting to see whether these effects also hold in other product categories for which consumers have less knowledge. Further, the present effects are observed with relatively short periods between the search trials. In reality, these periods may be much longer, and consumers will only search on the same shelf when they need to repurchase in the same category. Future research is necessary to see whether these memory effects still hold after several weeks, or even months. Another interesting avenue for future research would be to investigate how these memory effects accumulate over more than two search trials. An important question would be than whether brand search may become automatic, meaning that specific brands may 'pop-out' and would be located immediately (Alba and Hutchinson 1987).

The memory effects on the top-down weights affecting salience are interpreted by projecting these effects on the salience of the target brand. However, we could project these effects also on the salience of all other competing brands on the shelf. Similar to Chapter 3, we could do a competitive salience analysis to determine where the gained or lost salience due to memory comes from.

Further, this research related the number of fixations on the target and the distractor brands to target- and distractor-specific memory. However, eye-fixations are generated either in the localization or identification state. Since information acquisition during these attention states differ, it is possible that these fixations have a different effect on memory. This believe is supported by recent studies that show that within-trial memory is affected by spatial working memory but not by visual working memory (Oh and Kim 2004; Woodman and Luck 2004; Woodman et al. 2001). It is possible that these separate stores of working memory are both active during brand search, spatial working memory during the localization state, and visual working memory in the identification state. The present data set did not allow us to study these effects, because we had too few fixations in the identification state to reliably test these effects.

In the presented experimental data set, the positions of brands within and across consumers were similar. Therefore we were not able to disentangle location- and context-specific memory effects. Future research should investigate these important across-trial effects, as consumers frequently use location cues to locate brands.

The present study did not find any evidence for trial-to-trial priming. This is possibly due to the fact that consumers have sufficient time between the search trials to adapt their strategy based on the new target. However, in practice consumers might search immediately for a new target on the same retail shelf, when for example searching for different flavors of potato chips, or juices. In this case, search for a subsequent target might be influenced by trial-to-trial priming of the previous target.

Chapter 5

Conclusions and Directions for Future Research

5.1 Introduction

Consumers continuously search for products in stores, magazines, shopping windows, the Internet, or in their own kitchen. In the first chapter of this dissertation we showed that this brand search task is not trivial on large cluttered retail shelves. Consumers frequently complain that they cannot find what they want, leading to dissatisfaction with the retailer, or brand switching. The research presented in this dissertation is the first that investigated how consumers localize brands on displays. The conclusions from each chapter in this dissertation are summarized in the first section of this chapter, after which we provide implications of this research in the second section. Because brand search is a special case of visual search, which is an important research area in cognitive psychology, engineering, computer vision, neuroscience and other research fields, this section offers also implications for these areas, next to marketing. The final section discusses limitations of the research in this dissertation, which lead to directions for future research.

5.2 Summary

The Brand Search Model (Chapter 2)

Previous research on visual search stressed the importance of spatial uncertainty during search tasks. We argue that next to spatial uncertainty, the problem of reducing identity uncertainty plays a significant role as well, especially in tasks with complex stimuli such as brand search. These two uncertainties are reduced by two separate attention states: the localization state and the identification state. These two attention states are at the core of our brand search model. We propose that during these two attention states, consumers may use different strategies to reduce spatial and identity uncertainty respectively, leading to different patterns of eye fixations. In the localization state, attention is guided by a salience map and systematic strategies. The salience map, which plays an important role in many theories of visual search, is based on basic perceptual features such as colors, luminance, and edges. Systematic strategies depend on the layout of the shelf, and guide attention in a systematic pattern, such as horizontal or vertical zigzag. During the identification state, attention is redirected to the current selected brand in order to determine whether the brand is a target or distractor.

Based on this conceptual model of brand search, we formulate a dynamic spatial model that uncovers the latent attention processes during brand search using the eye-movement patterns of consumers executing a brand search task. Our brand search model allows for consumer heterogeneity and estimates the probability that a certain eye fixation will be positioned on a specific pixel. The choice of the pixel depends on the attention state, the previous sequence of fixation positions, and the characteristics of the pixel, i.e. to which brand it belongs, and its feature values, i.e. color, luminance, and edges. Using eye-movement data of consumers in a brand search task, we find that consumers switch frequently between the two attention states. Post-hoc analysis of the individual search strategies show that these different strategies relate significantly to the traditional search performance measures, search time and accuracy.

Interestingly, the inclusion of the two qualitatively different attention states: localization and identification in chapter 2, and the extraction of low-level perceptual features from its RGB-values may provide new insights into the aggregation of eye-movement data in other marketing research applications, as elaborated in section 5.3.2. Further, as section 5.3.2 explains, the two latent attention states also predicts possible nonlinear search slopes, i.e. the relationship between search time and number of items on the display that is often used in cognitive psychology to infer attention processes during visual search tasks, which is implicitly assumed to be linear (Wolfe 1998).

Decomposition of Brand Salience (Chapter 3)

Brands need to be visually salient in order to be found at the point of purchase. As the salience map is an important component of the brand search model, we determine for each brand its visual salience. Visual salience is determined by two components: a bottom-up or stimulus-based component, arising from visual properties of the packages on the shelf, and a top-down or memory-based component, which depends on the search goal and knowledge of the consumer. We suggest that in-store activities, such as packaging redesign, mainly influence the stimulus component, and out-of-store activities, such as advertising, mainly influence the memory component. By letting consumers search for different target brands on a shelf, the brand search model allows us to decompose brand salience into its stimulus-based and memory-based component. Our results show that both components play an important role in determining the visual salience of a brand on a shelf. Further, validation of the model confirms that brand salience relates to search performance, with higher salience leading to shorter search times and higher accuracies.

This chapter also gives insights of how brands compete for visual salience, since increased salience of one brand goes at the expense of a decrease of visual salience of other brands. Interestingly, our results show that salience competition may be asymmetric, meaning that when brand A gains visual salience at the expense of brand B when it becomes a target, it is not necessarily true that brand B gains visual salience at the expense of brand A when brand B becomes target.

An important contribution of chapter 3 is that it decomposes the salience map into its bottom-up and top-down component. Although visual salience is used frequently to explain eye-movements in visual scenes (Parkhurst et al. 2002; Peters, Iyer, Itti, and Koch 2005), the importance of the top-down component is often overlooked, which may incorrectly lead to conclusions that visual salience does not or only weakly relate to eye movements (Henderson, Brockmole, Castelhano, and Mack in press).

Incidental Learning Effects (Chapter 4)

During a brand search task, consumers see and reject many distractor brands. In chapter 4 we investigated whether consumers learn any information during these incidental brand exposures. An extensive literature review on memory effects during visual search shows ambiguous results. While many studies claim that participants incidentally learn information during the search task, other researchers claim that visual search is memoryless. Further, we find that memory may affect the brand search process in several ways. Based on the literature review we distinguish across-trial and within-trial memory effects. Across-trial memory effects consist of task-, target-, distractor-, location-, context-specific memory, and trial-to-trial priming. While within-trial memory is reflected in systematic search strategies, across-trial memory may affect the top-down feature weights, the number of repetitions in the identification state, and the systematic search strategies.

In an experiment where consumers search twice for a specific brand of coffee, we find consistently across the two target brands that consumers do have distractor specific memory. For both brands in the second search trial, we find that the target brand gets more salient when it was attended in the previous search trial. Our results also show that consumers do have target- and task specific memory, but these effects affect the search process differently for both targets. Next to these memory effects, we also find systematic differences for age, suggesting that older consumers are less efficient in brand search.

These findings suggest that packages do have an advertising effect, and that “being on the shelf” is important, even when the brand is not considered. This result may be another additional explanation for slotting allowances, i.e. the fees manufacturers pay when introducing a new product on a retailer’s shelf, as further explained in section 5.3.2.

5.3 Implications

In this section we first provide managerial implications of this dissertation and implications for marketing research. Because this research builds on theories of visual search and attention in cognitive psychology and neuroscience, we offer implications for these research streams as well.

5.3.1 Managerial Implications

As indicated in chapter 1, findability of a brand is important for both retailers and manufacturers. When consumers are not able to find quickly what they want, they are likely to switch from brand or store. The results of our experiments show that in well-known categories, i.e. coffee and laundry detergents, consisting of 12 to 16 SKUs, about 20% of the consumers are not able to find the right target within 10 seconds! This dissertation gives suggestions for both retailers and manufacturers to improve findability of certain brands.

First of all, across all experiments in this dissertation we find consistently that the visual salience of a package has a positive influence on search performance. In other words salient brands are found faster and more accurately. The brand search model indicates exactly which sources contribute to the visual salience of packages on a retail shelf. This is important information for package (re)-design in order to increase visual salience based on these sources. For example, our brand search model indicates exactly which colors are most important in determining brand salience. Further, the decomposition of brand salience into its stimulus- and memory-based components helps marketing managers to decide which marketing tools are most efficient in enhancing the salience of their brands. The stimulus-based component can be influenced by package design and in-store activities, while the memory-based component is mainly under control of out-of-store activities such as advertising. Examples of in-store activities are placing products at more salient positions, such as the eye-level (Drèze et al. 1994), or by locating brands on special displays such as counter displays, displays containing signs, special lightning or sound to increase visibility of promoted brands. Examples of out-of store activities are the campaigns of Heinz that communicated the diagnostic color green of their new ketchup packages, and Kimberly-Clark that, as described in chapter 1, supported the re-design of the Kotex brand with advertising and an online marketing campaign.

Next to suggestions of improving brand salience, the results in chapter 3 of this dissertation show that the visual brand saliencies are not independent of each other. This means that brands compete for visual salience and that the increase of visual salience of one brand goes at the expense of visual salience of a selection of other brands. Marketing managers should take these competitive salience effects into account, since it is possible to gain visual salience only from the most important competitors. Further, as this competition is asymmetric, it is possible to gain visual salience from competitors when consumers are searching for your brand, while it is not necessarily true that your brand is suppressed when consumers are looking for the competitor.

These competitive salience effects do not only affect competitors, but also line extensions. Our results show that when consumers are searching for one specific SKU of a brand, the other SKUs of the same brand may also benefit and become more salient due to package similarities. This implies that introductions of new line extensions may benefit from the salience of existing SKUs. However, marketing managers should take into account that too much similarity across line extensions may result in brand confusion and hence hurt findability of their brands. A competitive salience analysis provided by the results of the brand search model may therefore assist in designing packages for line extensions that are sufficiently dissimilar while still allowing for cross-over salience from the other SKUs of the same brand.

Brand search may also be used to investigate brand confusion, and to judge whether competitors use illegal package imitations strategies to gain sales from competitors, mainly market leaders. This illegal strategy may harm both the imitated brand and consumers (Foxman, Muehling, and Berger 1990), as the imitated brand may lose sales because consumers unintentionally buy a lower quality copycat, or consumers buy the copycat because they use visual cues to infer quality (Warlop and Alba 2004). Therefore, companies frequently go to court to sue the imitator, as was recently the case between Unilever and Ahold (Food Ingredients First 2005). However, demonstrating imitation is usually very difficult, and researchers have used tachistoscopic recognition tests (Kapferer 1995) or consumer reports (Foxman et al. 1990) for this purpose. Ideally one should test brand confusion behaviorally, and observe whether consumers buy actually the intended brand or the imitator (Foxman, Berger, and Cote 1992). The brand search task is therefore a useful task to demonstrate imitation strategies, as it shows similarities through salience and its relation to accuracy in a realistic setting.

5.3.2 Implications for Research in Marketing

Next to managerial implications, this dissertation provides several implications for research in marketing. First, because brand search is often a subtask in many other consumer tasks such as decision making, and information search, the findings of this dissertation have implications for these research areas. As suggested by research on stimulus-based choice, salient brands have a higher probability of being chosen (Chandon et al. 2002; Pieters and Warlop 1999). However, these studies do not show which factors influence brand salience, and how consumers find a specific brand on the shelf, while these factors are frequently important predictors of the final choice (Drèze et al. 1994; Hoyer 1984; Leong 1993). Hence, the brand search model, in particular its derived salience map, may therefore be an important predictor of brand choice in a stimulus-based setting. Further, since the brand search model characterizes the change in the focus of attention during a search task, it may assist in the development of such models for choice that are currently lacking (Bettman et al. 1998).

Second, the findings in chapter 4 show that consumers incidentally learn information about the attended packages during a brand search task, even when these attended brands are rejected. These memory effects are reflected in a higher salience of the attended brand when it becomes a target in a subsequent brand search task. This result suggests that packages on a retail shelf may serve as a short advertisement for the product, and may be a further rationale for slotting allowances. Slotting allowances are fees paid by manufacturers to retailers to introduce a new product in their store, and the total of such fees have recently been estimated to be over $10 billion in the United States (Richards and Petterson 2004). Although marketing research suggests that one of the reasons for slotting allowances is to compensate for the high risk of new product introductions, the existence of slotting allowances is still not well understood (Rao and Mahi 2003; Richards and Petterson 2004). Our findings, which shows that packages on a shelf may serve as short commercials, may be another motivation for the existence of slotting allowances.

Third, the results of chapter 3 and 4 indicate that brand search is a valuable tool to measure memory effects, while consumers are not explicitly asked to recall or recognize information. This has implications for research memory effects in advertising, as these effects are frequently implicit and hence explicit testing techniques such as brand recognition and recall frequently fail to find effects (see Lee 2002; Shapiro and Krishnan 2001). Further, the brand search model indicates which processes are affected, i.e. localization or identification, and gives therefore more detailed insights in the specific information that is stored in memory.

Fourth, this research has implications for the aggregation of eye-movement data in marketing studies. Previous research in marketing usually has aggregated the eye fixations at the package level (Chandon et al. 2002; Russo and Leclerc 1994), or at the level of visual elements in advertising, such as brand logo, pictorial, and text (Pieters and Wedel 2004; Wedel and Pieters 2000). This research shows that eye fixations are generated by different latent attention states: localization and identification, which implies that fixations should not be aggregated as they may serve different processing goals. Further, although eye-fixation analysis at the level of visual objects, such as pictures, text, or packages is managerially relevant, this research shows that basic perceptual features such as colors, luminance, and edges may be alternative explanatory variables of guidance of visual attention. This implies that modeling eye-movements at the feature level may give better insights in the underlying processes of attention and give a better explanation of why certain regions get more attention. The brand search model shows that these measures can be easily translated into managerially relevant regions, such as brand salience or identification fixations on the target brand. Further, an analysis at the fixated-pixel level allows more flexible investigations afterwards, as one can report the salience of any region of interest, like the brand, text, or pictorial.

Next to these implications for marketing research, the MCMC algorithm to estimate the statistical formulation of the brand search model contains several interesting features that may be applied to estimate more efficiently other Bayesian models in marketing. As Bayesian methods have become increasingly popular in marketing (Rossi and Allenby 2003), the next section provides some implications for the estimation of these models.

Implications for Bayesian Estimation Algorithms in Marketing

First, the individual parameters in our model have a truncated normal distribution. In such situations, sampling from the posterior distributions of the overall mean and variance of these truncated normal distributions becomes difficult, since the normalizing constant depends on these parameters. Although this problem can be solved by numerical integration (Boatwright et al. 1999), this method is time consuming. In this dissertation we used a relatively new method introduced by Griffiths (2004) to sample the overall mean and standard deviation from a truncated normal distribution by transforming the truncated variables to its non-truncated equivalents. The method is new to marketing, but may be potentially useful for many marketing applications that include truncated variables, such as stochastic frontier estimation (Dutta, Narasimhan, and Rajiv 1999), or in cases where parameters are restricted to avoid wrong signs of coefficients (Boatwright et al. 1999).

Second, the augmented variable Gibbs sampler, or slice sampler developed by Damien et al. (1999) is another convenient way to sample from nonstandard distributions. Although this method is not yet frequently applied in marketing, recently Paap et al. (2005) successfully applied this method to sample from a restricted covariance matrix in a choice task. However, since one needs to sample from a restricted area that can frequently only be computed numerically, one needs to apply an acceptance/rejection algorithm that may be slow. The acceptance/rejection algorithm presented by Neal (2003) and Frey (1997) is very efficient and easy to implement, as shown in the brand search model. We believe that this algorithm, as applied in this dissertation, is potentially useful in many other marketing research applications, as marketing models are often complex and give rise to nonstandard posterior distributions.

5.3.3 Implications for Research on Visual Search

The brand search model is built on theories of visual search and attention. These original theories are mainly derived from search on very simple stimuli using only search performance measures, speed and accuracy. Many of these researchers claim that future research should validate current search findings on realistic, complex stimuli such as brands on a retail shelf (Duncan and Humphreys 1989; Wolfe 1998). Since the brand search model is tested on realistic stimuli, we believe that the findings of this dissertation have implications for research on visual search.

Our first observation is that, especially in visual search for complex stimuli, location uncertainty is not the only uncertainty that needs to be reduced during visual search tasks. We propose and find evidence that during a search task identity uncertainty plays an important role as well. For that reason, attention switches between two latent attention states: localization and identification. This idea and finding has implications for the interpretation of search slopes, i.e. search time divided by the number of items on the display, which is frequently used to define search efficiency and pop-out (Duncan and Humphreys 1989; Treisman and Gelade 1980; Wolfe 1994). In reality, visual search experiments find a continuum of search slopes that makes them not straightforward to interpret (Wolfe 1998). According to Wolfe (1998), the search slope depends on the dwell time, i.e. the time that attention needs to process an item. Dwell time is a proxy for identification and therefore explains the magnitude of the search slope. Further, theories in visual search assume that this dwell time is constant for each item, which seems a plausible assumption in search for relatively simple homogeneous stimuli. However, the results of our model imply that the dwell time or the time to identify an object is not constant across items. The implication of a variable dwell-time due to the identification state is that search times may be non-linear in the number of items inspected, and this may eventually lead to non-linear search slopes. Non-linear search slopes have recently been reported by Michod et al. (2004), who find concave search slopes especially in search for more complex items, i.e. conjunctions, and when targets are absent. Although their explanation is that attentional guidance during search tasks only starts after some initial time (Michod et al. 2004), variable dwell times may be another explanation. For example, we will observe concave search slopes when the relative number of items with a long dwell time decreases as the number of items on the shelf increases.

A second implication for models of visual search is that attention may also be guided systematically. Although the existence of systematic search is long known (Monk 1984), it is surprising that only a few studies have examined it, and that no computational or statistical models that we know formally incorporate it. Because systematic search is more likely in complex search tasks (Horowitz and Wolfe 2003), this observation is especially relevant for search in complex, realistic tasks. When visual search becomes more systematic, it implies that salience becomes a less important predictor of search speed, and hence derivation of visual salience based on reaction times may be biased.

Finally, as most theories of visual search are derived only from search performance measures, speed and accuracy, this research shows that these measures may not uncover all the underlying search processes. As suggested by many researchers (Pashler 1998; Sanders and Donk 1996; Townsend 1990; Wolfe 1998), the same strategies may lead to different search performance measures, and different strategies may lead to the same search performance as well. Hence, research on visual search analyzes thousands of trials to reduce these effects, which is unrealistic in natural search situations since people do not get thousands of search opportunities (Wolfe 1998). The research presented in this dissertation shows that it is possible, using eye-movement patterns and our brand search model, to infer latent search processes in complex tasks using only one search trial across a hundred participants.

Therefore we believe that the brand search model is a useful tool to develop and test further theories of visual search.

5.4 Limitations and Directions for Future Research

This dissertation shows that brand search may be a difficult task for consumers, and that understanding the brand search process may assist marketers to improve their packaging, shelf layout, advertising, and other in and out-of store communication in order to enhance findability of their brands. However, there are still many questions that remain unanswered, which should be addressed in future research. This section provides several of these questions that involve issues that should be answered in future research in marketing on brand search, as well as issues that should be resolved by fundamental research on visual search.

5.4.1 Directions for Future Research in Marketing on Brand Search

The suggestions that we raise for future research in marketing can be divided into four categories that are discussed next.

1. Moderating Search Performance Factors

The research in this dissertation empirically tested the brand search model in a laboratory using search tasks on a 21-inch computer screen. Although we used a representative sample of consumers searching for existing products, we did not include several factors that may influence the brand search task outside the laboratory. An important factor that influences brand search in a retail store is the absolute position on the shelf, as for example products at eye-level are found easier (Drèze et al. 1994). This effect may be incorporated in the brand search model through the stimulus-based component of the salience map. Further, the absolute position on the shelf may also influence salience through the top-down or memory-based component, because stores frequently position specific brands on specific locations. For example, higher margin brands are usually at eye-level, and large and heavy packages are usually stored at the bottom of a shelf for logistic reasons. Consumers may use this knowledge while searching for specific brands, and hence give different weights to the salience map based on position. Future research could investigate these position effects by studying the eye-movements of consumers on larger screens, or even on real shelves using different eye-movement equipment. However, the question then becomes whether in such situations the eye-movement equipment, such as helmets, remains sufficiently unobtrusive. In these situations other measurement techniques, such as direct observation or verbal protocols may be reliable alternatives to test position effects separately (Hoyer 1984; Leong 1993; Russo and Leclerc 1994). This position information, in combination with brand search process parameters, such as brand salience and time in the identification state, could be used to combine salience and position effects in order to predict findability of brands on retail shelves.

Other factors, besides in-store and out-of-store communications, that could influence the search performance process are time pressure and task motivation, and the presence of other consumers when consumers are searching for a product. In a choice task using eye-movement data, Pieters and Warlop (1999) find that consumers use different scanning strategy depending on their motivation level and time pressure. These researchers show that under time pressure and lower task motivation consumers extract less information from a brand, which might suggest that they will spend less time on identification, leading to more mistakes. Further, Wolfe, Alvarez, and Horowitz (2000a) show that the effort of systematic search is much higher than salience-based strategies. This would suggest that, especially under time pressure, consumers use more salience-based rather than systematic search strategies. Next to time pressure and task motivation, the presence of other consumers could influence search processes as well. Recently, Argo, Dahl, and Manchanda (2005) showed that consumers use different selection strategies when buying products when they are in the presence of other consumers. It would be interesting to see whether and how these factors influence search strategies, and how this in turn would influence search performance.

2. *Extensions of the Brand Search Model*

A limitation of the brand search model is that during the identification state attention is guided by only redirecting its focus to the previous attended brand. In practice consumers may use different cues, such as brand logo, text, package color, or shape to decide whether a selected item is target or distractor. Knowing this information may be very useful for marketing managers to create diagnostic cues on their packages in order to improve search accuracy. Future research might incorporate this in the brand search model by defining specific package areas containing important information,

and use these as separate repetition variables instead of the brand image as in this research. This approach is similar as Pieters and Warlop (1999), who analyzed the eye movements of consumers on the brand name, pictorial, and ingredient information during a choice task. Another way to incorporate identification is at the feature level instead of at the object level, as the visual brain integrates basic features to perceive and recognize objects based on prior knowledge (Kersten, Mamassian, and Yuille 2004; Treisman and Gelade 1980). The integration of features into objects is highly complex, however recent research in computer vision used Bayesian theories of visual perception to integrate low level image features into objects (Kersten et al. 2004; Lee and Mumford 2003). This research stream frequently incorporates bottom-up image properties, such as luminance and colors, in the likelihood, and modifies this information using top-down template information in the brain, which is incorporated in the prior. In this case, posterior probabilities of for example object identitiy or location can be computed. Najemnik and Geisler (2005) used this idea to create optimal eye-movement strategies in visual search by computing for each possible target location the posterior probability that a location contained the target. Optimal eye-fixations were chosen at positions that maximized the posterior probability of locating the target. Although these researchers used an uninformative prior, it would be interesting to incorporate consumer knowledge into the prior as obtained by for example advertising, or previous product-related experiences.
By analyzing what features are processed in the identification state, we may get a better picture of what (combination) of features are used to identify target brands, and hence we might be better able to predict when consumers get confused and make mistakes.

In the identification state we assume that consumers only identify the target by acquiring information of one selected brand. In choice tasks, Pieters and Warlop (1999) show that consumers may rapidly acquire information by brand and by attribute. Identification in our model is incorporated using information acquisition by brand, as reflected by repetitive fixations on the selected brand in the identification state. However, one could imagine that consumers may identify a brand by comparing attributes across two, or more selected candidates. This strategy may prevail in particular when a consumer is searching for a specific SKU within a line extension of one brand. These SKUs frequently share many attributes, and consumers may use a attribute-based strategy to identify a brand, which results in inter-brand saccades, rather than repeated fixations as reflected by intra-brand saccades (Pieters and Warlop 1999). Future extensions of the brand search model should incorporate these comparative identification strategies, in order to get a better understanding of the identification state. This may possibly also lead to better predictions about brand confusion, as attribute-based identification strategies may suggest similarities.

Next to standard search performance measures, the current version of the brand search model only incorporates eye-fixation positions as indicators of the process. However, eye-movement analysis results in several other measures such as fixation durations, pupil dilation, and viewing distance for each eye fixation (the distance between the eye and the search display). Future research might consider including these measures in the brand search model as they could give more insights in the brand search process. Chapter 2 for example shows that in the identification state fixation durations tend to be shorter. Fixation durations might therefore be a useful indicator of whether a fixation is generated in the localization or identification state. Further, fixation durations may also serve as indicators of the specific strategy consumers are using. For example, Wolfe et al. (2000a) show that fixation durations in systematic search tend to be longer, while Pieters and Warlop (1999) find that fixation durations tend to be shorter when consumers are under time pressure. Next to fixation durations, pupil dilation may be incorporated to measure working load during the brand search task, which may be an indicator of the difficulty during the brand search task, when controlling for luminance differences (Porter, Troscianko, and Gilchrist 2003). Finally, the distance from the eye to the display may be another determinant whether a consumer is in the localization or identification state, as one might expect that this distance is closer during identification, since the consumer is looking for more detailed information. Further, this may also be a measure of brand liking, as consumers seem to approach stimuli they like and avoid stimuli they dislike (Chen and Bargh 1999).

Another aspect of the brand search model is the perceptual field, i.e. the region around the fixation position from which consumers acquire information. The brand search model assumes a bivariate normal distribution with a fixed diagonal covariance matrix across consumers and fixations to approximate the perceptual field. However, in practice the perceptual field may differ between and within fixations, and may be asymmetric as well in the viewing direction (Rayner 1998). The estimation of the size of the perceptual field in this research turned out to be computationally infeasible, because of the time consuming integrations over the perceptual field. Future research might focus on developing and applying computationally efficient algorithms to estimate the perceptual field during brand search. These perceptual field differences across consumers may than be another explanation for search efficiency, as consumers with a larger perceptual field are assumed to search faster (Sanders and Donk 1996).

Incorporation of basic features in the localization state is an issue for further investigation. Because package shapes, and sizes were relatively constant across brands in our experiments, colors and luminance were the most important features in our model. Although it is still not clear what visual elements may serve as basic features, it is likely that package shapes and sizes may guide attention as well (Wolfe and Horowitz 2004). Future research should investigate the importance of these other features in order to get better insights in how to increase salience and hence findability of brands on a shelf. The image processing literature, in combination with computational algorithms in Matlab, may be very useful to assist this research by computing relatively fast and easy these basic features (Gonzalez, Woods, and Eddins 2004).

Although the statistical formalization of the brand search model incorporates heterogeneity across consumers, it assumes that consumers do not switch their search strategy during a task, i.e. the saliency map, systematic search, and repetition parameters are constant within consumers across fixations. However, during a search task consumers may find out that their initial strategy is not successful, and therefore switch to another strategy. For example, a consumer searching for a specific brand of coffee using the color red may find out that this color is not diagnostic for this category and hence changes strategy by giving a higher weight to systematic search, or another feature which changes the shape of the salience map. Adding additional latent attention states is a possible approach to study strategy changes. For instance, we could split the localization state into a salience-based search state, and a systematic search state to study whether consumers switch to systematic search when they find out that their initial salience-based strategy is inefficient. Future research could investigate these dynamic effects to see whether and how consumers switch between strategies and how this affects search performance.

Finally, we believe it is interesting to incorporate stopping rules into the brand search model, i.e. when do consumers decide to give up searching. Recently, Wolfe, Horowitz, and Kenner (2005) showed that people may use different stopping rules based on their expectations of target presence. They show that observers miss up to 50% of the targets when searching for rare items in a baggage-screening task, i.e. searching for specific ‘tools’ in luggage. In the experiments presented in this dissertation, target brands were always available, and consumers only needed to localize its’ location. In practice, the target might not be present, and consumers need also to decide whether the target is not on the shelf when they cannot find it quickly.

3. Shelf- and Package-Design Optimization

Shelf- and package-design optimization are important topics in marketing, although empirical marketing studies on design issues are rare (Bloch 1995). The reason for this is that design and its effects are hard to measure. This research provides a method to measure the impact of package and product design on salience. RGB-values of pictures are used to measure colors, brightness, and edges, which could be a starting point to code product shapes as well. Our brand search model determines exactly which of these design elements influence salience and hence attract attention, which is an important goal in product and package design (Bloch 1995). Therefore we believe that the brand search model could be a starting point for future research to optimize packages and shelves in order to improve findability. Ideally, one would like to develop a model that simulates brand search behavior of consumers, based on the parameter estimates of the brand search model. Simulation of search behavior is a common approach in neuroscience in order to get a better understanding of attention processes in the brain, especially in comparison with realized eye-movement patterns (Itti in press). We believe that this approach is a promising direction for future research in order to simulate the effects of a package or shelf redesign on the search process, which in turn could be used to optimize certain objectives: such as salience, or ease of identification.

Diagnosticity of package cues is another direction for future research to determine the optimal design of packages on a retail shelf. As shown in chapter 2, the color blue is a diagnostic feature contained by the target brand Van Nelle (see figure 2.1). Consumers who gave more weight to this diagnostic color were faster and more accurate, because the target became more salient in this case. To determine feature diagnosticity objectively, the Attentional Engagement Theory of Duncan and Humphreys (1989; 1992) could be very useful. This theory states that search gets slower when 1. the similarity between targets and distractors increases, and 2. distractor heterogeneity increases. This idea has recently been successfully applied in marketing to optimize attention to feature ads based on similarities of the sizes of key design elements (Pieters, Wedel, and Zhang 2005). This could be extended to other relevant feature dimensions, such as color, luminance and shape (Rosenholtz 2001). However, high diagnosticity will not automatically lead to optimal package designs, as high diagnosticity may sometimes imply refraining from category codes. As chapter 4 shows, the search performance of Van Nelle is significantly worse than the search performance of Douwe Egberts (see also table 4.2), which contains the non-diagnostic category code color red.

4. Other Applications of The Brand Search Model

The brand search model describes the eye-movement patterns of consumers during a brand search task. Eye-movement analysis is an important instrument in many other marketing applications such as print advertising, commercials, and webpage design. Future research might apply the brand search model on these other eye-movement applications, to determine salient locations, or regions of interest based on image features. Since the brand search model decomposes the salience map into a stimulus-based and memory-based component, based on processing goals, the model could also be a starting point to derive the means of these processing goals. For example in advertising processing, consumer may have different goals such as memorization, learning, and appreciation (Wyer and Srull 1989), which lead to different eye-movement patterns (Pieters et al. 2005). Future research could extend the brand search model to determine the different latent processing goals based on different latent means corresponding to different goals. An idea to extend the model to uncover different means is to use a mixture model, where consumers are assigned to clusters having different goals.

The essence of the brand search model is that it predicts the position of occurrence, which are eye-fixations in a brand search task, given the previous sequence of occurrences and the characteristics of the spatial layout, which is the shelf in our brand search tasks. This idea could be used in any situation that describes where certain events will occur in space. For example, recently radio frequency identification (RFID) has been used to determine how shoppers move through a supermarket (Larson, Bradlow, and Fader 2005). In this technology RFID tags are connected to shopping carts and signal every 5 seconds its location. This information is useful to uncover how shoppers travel through supermarkets, and how these paths relate to purchases. The ultimate goal is than to design a store format that optimizes sales, or profit. Larson et al. (2005) state that future research should develop a model that describes the path in detail, and they suggest to "model travel as a series of 'blink-to-blink' choices", where each blink corresponds to the position of the shopping cart. The Bayesian modeling approach presented in this dissertation could be adjusted to model shopping paths in a straightforward way, where each blink corresponds to an eye-fixation.

Next to other applications of the analytical model, the brand search task could be a useful tool to measure or determine the effects of other marketing variables. Chapter 4 shows that through the memory-based component one can measure whether attending to a package in a previous task affects the brand search process. Attending to packages could be replaced by other marketing instruments, such as advertising, in-store promotions, and commercials. Further, instead of only search performance measures as process outcomes, we could also add other measures afterwards. An interesting measure would be perceived assortment variety, which is an important construct for retailers as this may determine store choice (van Herpen and Pieters 2002). As proposed by van Herpen and Pieters (2002), an interesting avenue for future research to measure perceived assortment variety is to investigate how assortment presentation influences this measure. In this respect brand search may be another determinant of a consumers' perceived variety, as the ease of finding a product may influence perceived variety.

5.4.2 Directions for Future Research on Visual Search

Next to suggestions for future marketing research, the results of this dissertation provide also ideas for future research on visual search. Most importantly, chapter 4 shows that although there are many studies on memory processes in visual search, there is still no consensus on whether people have and use memory during visual search tasks. Further, there are different forms of memory that may influence visual search, which are summarized in chapter 4. A limitation of these studies is that they investigate the different memory processes in isolation, while in real life they may interact. It is unclear which of these memory processes are strongest, and how they may interfere. Further, these memory processes are studied in situations where participants search many times (usually a few hundred to thousand trials) for similar simple stimuli. It is not clear how many trials are necessary, and how long these effects persist. We also observed that location-specific memory is largely ignored in this literature, reflected in the fact that Shore and Klein (2000) did not mention this form of memory in their review. Therefore, future research on visual search should try to extend existing models of visual search to incorporate the different memory effects that may occur across and within trials.

Finally, computational models of visual search and attention are getting more popular (Itti in press; Itti and Koch 2001; Pomplun et al. 2003). These models simulate visual attention during a visual search task by assuming several parameter inputs. The model outcomes are frequently compared with search outcomes of participants. Future research in this area could benefit from our brand search model by choosing a reasonable range for the parameter input. For example, salience is an important input variable in these models, which is explicitly estimated in our model. These estimates could be useful input for these computational models to provide better insights in the visual search process.

In conclusion, this dissertation is the first to investigate one of the most common activities consumers face in everyday life: brand search. Eye-tracking data in combination with a sophisticate statistical model has proven to provide detailed insights into the brand search process. It is our hope that this dissertation encourages more research in this area, which will hopefully lead to guidelines for retailers and manufacturers to design better packages, shelves and marketing programs that will help us, consumers, to find our products more easily.

Appendix A

Derivation of the Truncated Region

As described in chapter 2, the consumer specific parameters $\theta_{cj,-1}$ are generated from a truncated normal distribution with overall mean μ_j and diagonal variance matrix Σ_j. Consequently, the conditional posterior distributions of μ_j and Σ_j are nonstandard because the normalizing constant depends on these parameters (Boatwright et al. 1999). The method of Griffiths (2004) that we use in this thesis, transforms the individual truncated parameters $\theta_{cj,-1}$ to their non-truncated equivalent (see equation 7 in chapter 2), which gives standard posterior distributions for μ_j and Σ_j, and hence sampling these parameters becomes straightforward. However, this procedure requires the exact truncation points $a_{ck}\left(\theta_{jc,-\{1,k\}}\right)$ and $b_{ck}\left(\theta_{jc,-\{1,k\}}\right)$, which are not straightforward in our algorithm. This Appendix derives these truncation points deterministically, which occur because of 1) the square root link function, and 2) the fact that the total intensity integrates to one (see equation 2.2 in chapter 2). Note that to assure unique solutions we restricted the constant to be positive.

We standardized the data in such a way that $\left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=1$ if variable *k* exists on the display for fixation *i*, and $\left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=0$ otherwise. Note, that the situation $\left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=0$ may occur for the dynamic variables (for example, the dummy repetition takes the value zero on the whole display when the previous eye-fixation *i*-1 was not on a specific brand). Taking in mind these simplifications, we can express the constant θ_{cj1i} as follows:

$$\theta_{cj1i}\left(\theta_{cjk}\right)=\begin{cases}\alpha_{ci1}\theta_{cjk}+\alpha_{ci2}^{j}+\sqrt{\alpha_{ci3}\theta_{cjk}^{2}+\alpha_{ci4}^{j}\theta_{cjk}+\alpha_{ci5}^{j}} & \text{if } \left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=1\\ 1 \text{ otherwise}\end{cases} \tag{A1}$$

with:

$$\alpha_{ci1} = -\left(\mathbf{s}_{F_{c,i-1}}\right)_{1k} \tag{A2.1}$$

$$\alpha_{ci2}^{j} = -\sum_{j\notin\{1,k\}}^{m}\left(\mathbf{s}_{F_{c,i-1}}\right)_{1j}\theta_{cj} \tag{A2.2}$$

$$\alpha_{ci3} = \left(\mathbf{s}_{F_{c,i-1}}\right)_{1k}^{2}-1 \tag{A2.3}$$

$$\alpha_{ci4}^{j} = 2\sum_{r\notin\{1,k\}}\left(\left(\mathbf{s}_{F_{c,i-1}}\right)_{1j}\left(\mathbf{s}_{F_{c,i-1}}\right)_{1k}-\left(\mathbf{s}_{F_{c,i-1}}\right)_{rk}\right)\theta_{cr} \tag{A2.4}$$

$$\alpha_{ci5}^{j} = 1+\sum_{r\notin\{1,k\}}\left(\left(\mathbf{s}_{F_{c,i-1}}\right)_{1r}^{2}-\left(\mathbf{s}_{F_{c,i-1}}\right)_{rr}\right)\theta_{cr}^{2}+ \sum_{r\notin\{1,k\}}\sum_{l\notin\{1,k,r\}}\left(\left(\mathbf{s}_{F_{c,i-1}}\right)_{1r}\left(\mathbf{s}_{F_{c,i-1}}\right)_{1l}-\left(\mathbf{s}_{F_{c,i-1}}\right)_{rl}\right)\theta_{cr}\theta_{cl} \tag{A2.5}$$

In the remaining part of the appendix we assume that $\left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=1$, since $\left(\mathbf{s}_{F_{c,i-1}}\right)_{kk}=0$ will not lead to any restrictions on the corresponding parameter θ_{cjk}. From (A1) it follows that we may only chose θ_{cjk} in such a way that $\theta_{cj1i}\left(\theta_{cjk}\right)$ is defined. This results in the following restriction (A3) for the parameter space of θ_{cjk}, while taking into account that $\alpha_{ci3}<0$.

$$\frac{-\alpha_{ci4}^{j}+\sqrt{\alpha_{ci4}^{j\,2}-4\alpha_{ci3}\alpha_{ci5}^{j}}}{2\alpha_{ci3}}<\theta_{cjk}<\frac{-\alpha_{ci4}^{j}-\sqrt{\alpha_{ci4}^{j\,2}-4\alpha_{ci3}\alpha_{ci5}^{j}}}{2\alpha_{ci3}} \tag{A3}$$

This allowed region (A3) for θ_{cjk} may lead to non-unique solutions we therefore restrict $\theta_{cj1i}>0,\forall i=1,..,n_c$, i.e. the constant becomes the 'reflective parameter. Solving $\theta_{cj1i}\left(\theta_{cjk}\right)=0$ leads to the following two possible solutions:

$$\theta_{cjk} = \frac{2\alpha_{ci1}\alpha_{ci2}^{j}-\alpha_{ci4}^{j}-\sqrt{-4\alpha_{ci1}\alpha_{ci2}^{j}\alpha_{ci4}^{j}+\alpha_{ci4}^{j\,2}+4\alpha_{ci3}\alpha_{ci2}^{j\,2}-4\alpha_{ci3}\alpha_{ci5}^{j}+4\alpha_{ci1}^{2}\alpha_{ci5}^{j}}}{2\left(\alpha_{ci3}-\alpha_{ci1}^{2}\right)} \tag{A4.1}$$

$$\theta_{cjk} = \frac{2\alpha_{ci1}\alpha_{ci2}^{j}-\alpha_{ci4}^{j}+\sqrt{-4\alpha_{ci1}\alpha_{ci2}^{j}\alpha_{ci4}^{j}+\alpha_{ci4}^{j\,2}+4\alpha_{ci3}\alpha_{ci2}^{j\,2}-4\alpha_{ci3}\alpha_{ci5}^{j}+4\alpha_{ci1}^{2}\alpha_{ci5}^{j}}}{2\left(\alpha_{ci3}-\alpha_{ci1}^{2}\right)} \tag{A4.2}$$

Using (A4.1) and (A4.2) in combination with (A3) we are able to determine the exact truncation points of region R_c.

Appendix B

Transforming Truncated Normal Variables to Their Normal Equivalent

In the MCMC-estimation algorithm of the brand search model we need to compute the mean and standard deviation of a truncated normal variable. This is a complicated problem, since the normalizing constant also depends on the unknown mean and standard deviation. Boatwright, McCulloch, and Rossi (1999) solve this problem by approximating the normalizing constant using the GHK method to compute the integral corresponding to the normalizing constant. This method is time-consuming, especially when thousands of normalizing constants need to be computed per iteration. Recently, Griffiths (2004) solved this problem in a different way by transforming the truncated variables to its non-truncated equivalents (see Theorem below). Although Griffiths provides a proof of this method, in this appendix we give two additional proofs of this method: the first proof is based on simulation results of 10.000 draws, the second proof is based on the CDF-method for transforming random variables.

Theorem:

Suppose θ is truncated Normal distributed with mean μ, standard deviation σ, and truncation points a and b, and let $\theta^* = h(\theta) = \mu + \sigma \cdot \Phi^{-1}\left(\frac{\Phi\left(\frac{\theta-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)}{\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)} \right)$, than θ^* is normally distributed with mean μ, standard deviation σ.

Proof 1: Simulation

Suppose $\mu = 0$, $\sigma = 1$, $a = 0$, and $b = \infty$, than $\theta^* = \Phi^{-1}\left(\frac{\Phi(\theta)-\Phi(0)}{\Phi(1)-\Phi(0)}\right) = \Phi^{-1}\left(\frac{\Phi(\theta)-0.5}{0.5}\right)$.

We used this formula to transform θ to θ^*, where θ is truncated Normal distributed.

Table B.1 *Simulation results for different a and b values*[1,2]

	b = -1.5		b = 0		b = 1.5		$b = \infty$	
	$(\hat{\mu}-\mu)$	$(\hat{\sigma}-\sigma)$	$(\hat{\mu}-\mu)$	$(\hat{\sigma}-\sigma)$	$(\hat{\mu}-\mu)$	$(\hat{\sigma}-\sigma)$	$(\hat{\mu}-\mu)$	$(\hat{\sigma}-\sigma)$
a = -∞	1.10	-0.69	-0.51	-0.85	0.40	0.42	0.73	-0.18
a = -3.0	-0.01	0.49	0.42	-1.00	0.94	-1.21	-0.25	-0.06
a = -1.5	-	-	0.74	1.27	-1.3	0.06	-0.45	-0.03
a = 0	-	-	-	-	0.33	0.86	-1.66	0.39
a = 1.5	-	-	-	-	-	-	-0.32	-0.33
a = 3	-	-	-	-	-	-	1.06	-0.82

1 All deviations multiplied by 100
2 In the simulations $\mu = 0$ and $\sigma = 1$

Proof 2: Using method described in Arnold (1990 p. 58)

The range of θ is $[a,b]$, consequently the range of θ^* is $[-\infty,\infty]$ (since $h(a) = -\infty$, and $h(b) = \infty$). Further we assume for simplicity that (assuming $\mu = 0$, $\sigma = 1$)

$$
\begin{aligned}
F_{\Theta^*}(\theta^*) &= P(\Theta^* \le \theta^*) = P(h(\Theta) \le \theta^*) = P(\Theta \le h^{-1}(\theta^*)) \\
&= P\left(\Phi^{-1}\left(\frac{\Phi(\Theta)-\Phi(a)}{\Phi(b)-\Phi(a)}\right) \le \theta^*\right) \\
&= P\left(\Theta \le \Phi^{-1}\left[\Phi(a)+\Phi(\theta^*)\{\Phi(b)-\Phi(a)\}\right]\right) \\
&= \int_a^{\Phi^{-1}\left[\Phi(a)+\Phi(\theta^*)\{\Phi(b)-\Phi(a)\}\right]} \frac{1}{\Phi(b)-\Phi(a)} \varphi(\theta) d\theta \\
&= \frac{\Phi(\theta)}{\Phi(b)-\Phi(a)} \Big|_a^{\Phi^{-1}\left[\Phi(a)+\Phi(\theta^*)\{\Phi(b)-\Phi(a)\}\right]} \\
&= \frac{\Phi(a)+\Phi(\theta^*)\{\Phi(b)-\Phi(a)\}}{\Phi(b)-\Phi(a)} - \frac{\Phi(a)}{\Phi(b)-\Phi(a)} = \Phi(\theta^*)
\end{aligned}
$$

which is the normal distribution.

Appendix C

MCMC Algorithm Chapter 3

This section describes the MCMC algorithm to estimate the model. For this procedure we specified the following diffuse prior distributions: $\mu_j \sim N\left(\eta_{j0}, H_{j0}\right)$, $\tau_{jg} \sim N\left(\eta_{jg}, H_{jg}\right)$, $\Sigma_j \sim W\left(D_j, d_j\right)$, $\Pi \sim D(\Xi)$, $\beta_{perf} = \begin{pmatrix} \beta_{time} \\ \beta_{acc} \end{pmatrix} \sim N\left(b_{perf}, B_{perf}\right)$, $\Sigma^{Perf^{-1}} \sim W\left(D^{perf}, d^{perf}\right)$ with $\eta_{j0} = \eta_{jg} = \mathbf{0}$, $H_{j0} = H_{jg} = 10^4 \cdot I$, $D_j = 10 \cdot I_{K_j}$, $d_j = K_j + 2$, and $\Xi = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$, $b_{perf} = \mathbf{0}$, $B_{perf} = 10^3 \cdot I$, $d^{perf} = 3$, $D^{Perf} = 10 \cdot I_2$ $\forall j = \{1,2\}$, $g = \{1,..,G-1\}$, and $k_j = \{2,..,K_j\}$, where K_j is the number of variables in state j, and K_j^m the number of variables representing the salience map consisting of stimulus-based and consumer-based effects. Using these priors, we sampled the parameters sequentially from the following posterior distributions:

1.
$$z_{ci} \mid .. \sim MN\left(\frac{\pi_{z_{c,i-1},1} \cdot \left(x_{ci}{}'\theta_{c(j=1)}\right)^2 \cdot p\left(y_c^{time}, y_c^{acc}\right) \cdot \pi_{1,z_{c,i+1}}}{\sum_{j=1}^{2} \pi_{z_{c,i-1},j} \left(x_{ci}{}'\theta_{cj}\right)^2 p\left(y_c^{time}, y_c^{acc}\right) \cdot \pi_{j,z_{c,i+1}}}, \frac{\pi_{z_{c,i-1},2} \cdot \left(x_{ci}{}'\theta_{c(j=2)}\right)^2 \cdot p\left(y_c^{time}, y_c^{acc}\right) \cdot \pi_{2,z_{c,i+1}}}{\sum_{j=1}^{2} \pi_{z_{c,i-1},j} \left(x_{ci}{}'\theta_{cj}\right)^2 p\left(y_c^{time}, y_c^{acc}\right) \cdot \pi_{j,z_{c,i+1}}} \right)$$

where $p\left(y_c^{time}, y_c^{acc}\right)$ represents the pdf of the multivariate performance regression (Robert et al. 1993).

2. For drawing θ_{cjk}, we apply the auxiliary variable Gibbs sampler (Damien et al. 1999) , using the procedure described in (Neal 2003) to determine the slice. This results in the sampling of the following auxiliary variables: $u_{ci1}^{j} \mid .. \sim U\left(0, \left|x_{ci}{}' \cdot \theta_{cj}\right|\right)$, $u_{ci2}^{j} \mid .. \sim U\left(0, \left|x_{ci}{}' \cdot \theta_{cj}\right|\right)$, $u_{c}^{perf} \mid .. \sim p\left(y_{c}^{time}, y_{c}^{acc}\right)$, and the target parameters

$$\theta_{cjk} \mid ... \sim N\left(\mu_{jk} + \tau_{j,group(c),k}, \Sigma_{jkk}\right) \cdot I\left\{\max\left\{u_{ci1}^{j}, u_{ci2}^{j}\right\} < \left|x_{ci} \cdot \theta_{cj}\right| \forall i : z_{ci} = j\right\} \cdot$$
$$I\left\{u_{c}^{perf} < p\left(y_{time}, y_{acc}\right)\right\}.$$

3. Because θ_{cjk} is truncated normally distributed, we cannot directly sample their overall means and variances. Therefore we transform θ_{cjk} into its non-truncated equivalent (assuming that consumer *c* is a member of group *g*):

$$\vartheta_{cjk} = \mu_{jk} + \tau_{jgk} + \sigma_{jk} \cdot \Phi^{-1}\left(\frac{\Phi\left(\frac{\theta_{cjk} - \left(\mu_{jk} + \tau_{jgk}\right)}{\sigma_{jk}}\right) - \Phi\left(\frac{a_{ck}\left(\theta_{cj,-\{1,k\}}\right) - \left(\mu_{jk} + \tau_{jgk}\right)}{\sigma_{jk}}\right)}{\Phi\left(\frac{b_{ck}\left(\theta_{cj,-\{1,k\}}\right) - \left(\mu_{jk} + \tau_{jgk}\right)}{\sigma_{jk}}\right) - \Phi\left(\frac{a_{ck}\left(\theta_{cj,-\{1,k\}}\right) - \left(\mu_{jk} + \tau_{jgk}\right)}{\sigma_{jk}}\right)}\right)$$

(Griffiths 2004), with $a_{ck}(.)$ the lower, and $b_{ck}(.)$ the upper truncation points for θ_{cjk} respectively. Using ϑ_{cjk} results in the following posteriors

$$\mu_{j0} \mid .. \sim N\left(Q_{j0}\left(\Sigma_{j}^{-1}\left(\sum_{c=1}^{C} \widetilde{\vartheta_{jc0}}\right) + H_{jg}^{-1}\eta_{jg}\right), Q_{j0}\right),$$

$\tau_{jg} \mid .. \sim N\left(Q_{jg}\left(\Sigma_{j}^{-1}\left(\sum_{c=1}^{C} \widetilde{\vartheta_{jcg}}\right) + H_{jg}^{-1}\eta_{jg}\right), Q_{jg}\right)$, where $Q_{j0} = \left(C \cdot \Sigma_{j}^{-1} + H_{j}^{-1}\right)$, and

$Q_{jg} = \left(\left(C_{g} + C_{G}\right) \cdot \Sigma_{j}^{-1} + H_{j}^{-1}\right)$, with C_{g} the number of consumers assigned to search task *g*. Further, $\widetilde{\vartheta_{jc0}} = \begin{cases} \vartheta_{jc} - \tau_{j,group(c)} & \text{if } group(c) < G \\ \vartheta_{jc} + \sum_{g=1}^{G-1} \tau_{jg} & \text{if } group(c) = G \end{cases}$, and

$$\widetilde{\vartheta_{jcg}} = \begin{cases} 0 & \text{if } group(c) \notin \{g, G\} \\ \vartheta_{jc} - \mu_{j} & \text{if } group(c) = g \\ -\left(\vartheta_{jc} - \mu_{j} + \sum_{g'=1, g' \neq g}^{G-1} \tau_{jg'}\right) & \text{if } group(c) = G \end{cases}.$$

4. $$\Sigma_j^{-1} \mid .. \sim W\left(\sum_{c=1}^{C} \left(\vartheta_{cj} - \left(\mu_j + \tau_{j,group(c)} \right) \right) \left(\vartheta_{cj} - \left(\mu_j + \tau_{j,group(c)} \right) \right)' + D_j^{-1}, C + d_j \right).$$

5. $$\Pi \mid .. \sim D \begin{pmatrix} \xi_{11} + \sum_{c=1}^{C} \sum_{i=2}^{n_c} I\{z_{ci-1} = 1\} \cdot I\{z_{ci} = 1\} & \xi_{12} + \sum_{c=1}^{C} \sum_{i=2}^{n_c} I\{z_{ci-1} = 1\} \cdot I\{z_{ci} = 2\} \\ \xi_{21} + \sum_{c=1}^{C} \sum_{i=2}^{n_c} I\{z_{ci-1} = 2\} \cdot I\{z_{ci} = 1\} & \xi_{22} + \sum_{c=1}^{C} \sum_{i=2}^{n_c} I\{z_{ci-1} = 2\} \cdot I\{z_{ci} = 2\} \end{pmatrix}.$$

6. For the search performance parameters β_{time} and β_{acc} we apply the method of Chib and Greenberg (1998) to estimate multivariate probit models, and therefore allow estimating restricted covariance matrices. We first generate the latent variables V as follows:

$$V_c \mid .. \sim \begin{cases} TN_{>0}\left(F\beta_{acc} + \dfrac{\sigma_{12}^{perf}}{\sigma_{11}^{perf}} \left(y_{time} - F\beta_{time} \right), \left(1 - \dfrac{\left(\sigma_{12}^{perf}\right)^2}{\sigma_{11}^{perf}} \right)^{1/2} \right) & \text{if } y_{acc,c} = 1 \\ TN_{<0}\left(F\beta_{acc} + \dfrac{\sigma_{12}^{perf}}{\sigma_{11}^{perf}} \left(y_{time} - F\beta_{time} \right), \left(1 - \dfrac{\left(\sigma_{12}^{perf}\right)^2}{\sigma_{11}^{perf}} \right)^{1/2} \right) & \text{if } y_{acc,c} = 0 \end{cases},$$

with $F = \left[1 \, f_1(\theta, z) \, f_2(\theta, z) \ldots f_7(\theta, z) \right]$ as defined in section 4.4. Using these latent variables V, we compute β_{time} and β_{acc} as follows:

$$\begin{pmatrix} \beta_{time} \\ \beta_{acc} \end{pmatrix} \sim N\left(Q_{perf} \left(\left(I_2 \otimes F \right)' \left(\Sigma^{perf^{-1}} \otimes I_C \right) \begin{pmatrix} y_{time} \\ V \end{pmatrix} + B_{perf}^{-1} b_{perf} \right), Q_{perf} \right), \text{ with}$$

$$Q_{perf} = \left(\left(I_2 \otimes F \right)' \left(\Sigma^{perf^{-1}} \otimes I_C \right) \left(I_2 \otimes F \right) + B_{perf}^{-1} \right)^{-1}.$$ Because the prior and the likelihood are not conjugate, we use a Metropolis-Hastings step to generate Σ^{perf}, as proposed by Chib and Greenberg (1998).

Appendix D

MCMC Algorithm Chapter 4

Similar as in the brand search model in Chapter 3, the individual weights θ_{ctjk}^{g} are influenced by bottom up μ_{jk} and top-down τ_{cjt}^{g} processes. We extended this model by allowing the top-down effects to depend on consumer characteristics, such as gender and age, and on process outcomes of previous brand search trials $t = 1,..,T$ by the same consumer. This leads to the following distribution of the individual parameters θ_{ctjk}^{g} [1]:

$$\theta_{ctjk}^{g} \sim N\left(\mu_{jk} + \tau_{cjt}^{g}, \Sigma_{jkk}\right), \text{ with } \tau_{cjt}^{g} = \begin{cases} \tau_{j}^{g} + \sum_{r \in 1}^{R} \upsilon_{jkr}^{g} w_{ctr} & \text{if } t = 1 \\ \tau_{j}^{g} + \sum_{r=1, r \neq 4}^{R} \upsilon_{jkr}^{g} w_{ctr} + \upsilon_{jk4} \theta_{c,t-1,jk}^{g'} & \text{if } t > 1 \end{cases},$$

where $g = g_{ct}$, and $g' = g_{c,t-1}$ corresponds to the target brand that consumer *c* faced in task *t*, and *t-1* respectively. w_{cr} corresponds to consumer specific variables that may influence top-down effects (i.e, the consumer specific characteristics and the across-trial memory effects in equation 1, which equal zero for $t = 1$). Further, $\theta_{c,t-1,jk}^{g'}$ corresponds to the priming effect. Note that the priming effect is similar across search targets. This extension leads to the following MCMC algorithm[2]:

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[1] We use the notation of the original brand search model, so that $\theta_{ctjk}^{g} = \psi_{ctm}^{g}$ for $k \in K_{m}$, i.e. the variables corresponding to the salience map, and $\theta_{ctjk}^{g} = \omega_{cts}^{g}$ for $k \in K_{s}$ corresponding to the systematic strategies.

[2] Note: we only derive posterior distributions that change due to the extension. For the derivation of the remaining parameters we refer to Chapter 3.

1. z_{cti} indicates the state (localization: $z_{cti} = 1$, or identification: $z_{cti} = 2$) from which an eye fixation *i* of consumer *c* in task *t* is generated. The posterior distribution of z_{cti} is as follows:

$$z_{cti} \mid .. \sim MN\left(\frac{\pi_{z_{ct,i-1},1} \cdot \left(x_{cti}'\theta_{ct(j=1)}\right)^2 \cdot p_{perf}\left(z_c\right) \cdot p_{id}\left(z_c\right) \pi_{1,z_{ct,i+1}}}{\sum_{j=1}^{2} \pi_{z_{ct,i-1},j} \left(x_{cti}'\theta_{ctj}\right)^2 p_{perf}\left(z_c\right) \cdot p_{id}\left(z_c\right) \cdot \pi_{j,z_{ct,i+1}}}, \frac{\pi_{z_{ct,i-1},2} \cdot \left(x_{cti}'\theta_{ct(j=2)}\right)^2 \cdot p_{perf}\left(z_c\right) \cdot p_{id}\left(z_c\right) \cdot \pi_{2,z_{ct,i+1}}}{\sum_{j=1}^{2} \pi_{z_{ct,i-1},j} \left(x_{cti}'\theta_{ctj}\right)^2 p_{perf}\left(z_c\right) \cdot p_{id}\left(z_c\right) \cdot \pi_{j,z_{ct,i+1}}} \right)$$

where $p_{perf}\left(z_c\right)$ represents the pdf of the multivariate performance regression (see step 7), and $p_{id}\left(z_c\right)$ the regression on the number of identification fixations on the target (see step 8).

2a. For drawing θ^g_{ctjk}, we need to take into account that the top-down mean τ^g_{cjt} is consumer specific, and that except for the first task, this mean depends on the drawings of $\theta^g_{c,t-1,jk}$ previous tasks $t-1$. Since the parameters of the last task *T* do not influence other parameters, this posterior distribution is similar as the one presented in Chapter 3, and is as follows: draw $u^j_{cTi1} \mid .. \sim U\left(0, \left|x_{cTi}' \cdot \theta^g_{cTj}\right|\right)$, $u^j_{cTi2} \mid .. \sim U\left(0, \left|x_{cTi}' \cdot \theta^g_{cTj}\right|\right)$, $u^{perf}_{cT} \mid .. \sim p\left(y^{time}_{cT}, y^{acc}_{cT}\right)$, and the target parameters $\theta^g_{cTjk} \mid ... \sim N\left(\mu_{jk} + \tau^g_{cTjk}, \Sigma_{jkk}\right) \cdot I\left\{\max\left\{u^j_{cTi1}, u^j_{cTi2}\right\} < \left|x_{cTi} \cdot \theta^g_{cTj}\right| \forall i : z_{cTi} = j\right\} \cdot$

$$I\left\{u^{perf}_{cT} < p\left(y^{time}_{cT}, y^{acc}_{cT}\right)\right\}.$$

2b. Since for $t < T$, θ^g_{ctjk} influences $\tau^g_{c,t+1,jk}$, its posterior distribution is as follows (for simplicity in notation we assume $T = 2$, $\theta^g_{ctjk} = \theta_t = \theta_1$, $\theta^g_{cTjk} = \theta_T = \theta_2$, $\mu_{jk} + \tau^g_{ctjk} = \mu_1$, $\mu_{jk} + \tau^g_{cTjk} = \mu_2$, $\Sigma_{jkk} = \sigma^2$, for the derivation):

$$\theta_1 \mid ... \propto \exp\left(-\frac{\left(\theta_1 - \mu_1\right)^2}{2\sigma^2}\right) \cdot \exp\left(-\frac{\left(\theta_2 - \mu_2\left(\theta_1\right)\right)^2}{2\sigma^2}\right) \cdot K\left(\theta_1\right) \qquad \text{(D1)}$$

with $\mu_2\left(\theta_1\right) = \mu_{jk} + \tau^g_j + \sum_{r=1}^{R} \upsilon^g_{jkr} w_{ctr} + \upsilon_{jk4}\theta_1 = c_2 + \upsilon_4\theta_1$, and $K\left(\theta_1\right) = \prod_{i:z_{cTi}=j}^{n_{cT}} \left(x_{cTi}'\theta_1\right)^2 \cdot k_2^{-1}\left(\theta_1\right)$, with $k_2^{-1}\left(\theta_1\right)$ representing the normalizing constant of task 2, that is now a function of θ_1. Equation D1 can be simplified as follows:

$$\theta_1 \mid ... \propto \exp\left(-\frac{\theta_1^2 - 2\theta_1\mu_1 + \upsilon_4^2\theta_1^2 - 2\upsilon_4\theta_1\left(\theta_2 - c_2\right)}{2\sigma^2} \right) \cdot K\left(\theta_1\right),$$

$$\theta_1 \mid ... \propto \exp\left(-\frac{\left(1+\upsilon_4^2\right)\theta_1^2 - 2\theta_1\left(\mu_1 + \upsilon_4\left(\theta_2 - c_2\right)\right)}{2\sigma^2} \right) \cdot K\left(\theta_1\right),$$

$$\theta_1 \mid ... \propto \exp\left(-\frac{\theta_1^2 - 2\theta_1 \dfrac{\mu_1 + \upsilon_4\left(\theta_2 - c_2\right)}{1+\upsilon_4^2}}{2\dfrac{\sigma^2}{1+\upsilon_4^2}} \right) \cdot K\left(\theta_1\right) \qquad \text{(D2)}$$

Equation D2 corresponds to a truncated normal distribution with mean $\dfrac{\mu_1 + \upsilon_4\left(\theta_2 - c_2\right)}{1+\upsilon_4^2}$, and variance $\dfrac{\sigma^2}{1+\upsilon_4^2}$. Applying the auxiliary variable Gibbs sampler as in 2a results in the following draws: $u_{cti1}^{j} \mid .. \sim U\left(0, \left| x_{cti}' \cdot \theta_{ctj}^{g} \right|\right)$, $u_{cti2}^{j} \mid .. \sim U\left(0, \left| x_{cti}' \cdot \theta_{ctj}^{g} \right|\right)$, $u_{ctj3} \mid .. \sim -\log\left(\int_{R_{cTk}} \phi\left(y \mid \mu_{jk} + \tau_{cTjk}^{g}\left(\theta_{ctjk}^{g}\right), \Sigma_{jkk}\right) dy \right) - \exp(1)$, $u_{cT}^{perf} \mid .. \sim p\left(y_{cT}^{time}, y_{cT}^{acc}\right)$, and the target parameters

$$\theta_{ctjk}^{g} \mid ... \sim N\left(\frac{\mu_1 + \upsilon_4\left(\theta_2 - c_2\right)}{1+\upsilon_4^2}, \frac{\sigma^2}{1+\upsilon_4^2} \right) \cdot I\left\{ \max\left\{u_{cti1}^{j}, u_{cti2}^{j}\right\} < \left| x_{cti} \cdot \theta_{ctj}^{g} \right| \forall i : z_{cti} = j \right\}$$

$$I\left\{ u_{ctj4} < k_2\left(\theta_{ctjk}^{g}; \mu_{jk}, \tau_{ctjk}^{g'}, \Sigma_{jkk}^{B}\right)^{-1} \right\} \cdot I\left\{ u_{ct}^{perf} < p\left(y_{ct}^{time}, y_{ct}^{acc}\right) \right\}.$$

3. Because θ_{ctjk}^{g} is truncated normally distributed, we transform it into its non-truncated equivalent (see Chapter 3 and Griffiths (2004)):

$$\vartheta_{ctjk}^{g} = \mu_{jk} + \tau_{ctjk}^{g} + \sigma_{jk} \cdot \Phi^{-1}\left(\frac{ \Phi\left(\dfrac{\theta_{ctjk}^{g} - \left(\mu_{jk} + \tau_{ctjk}^{g}\right)}{\sigma_{jk}} \right) - \Phi\left(\dfrac{a_{ck}\left(\theta_{ctj,-\{1,k\}}^{g}\right) - \left(\mu_{jk} + \tau_{ctjk}^{g}\right)}{\sigma_{jk}} \right) }{ \Phi\left(\dfrac{b_{ck}\left(\theta_{ctj,-\{1,k\}}^{g}\right) - \left(\mu_{jk} + \tau_{ctjk}^{g}\right)}{\sigma_{jk}} \right) - \Phi\left(\dfrac{a_{ck}\left(\theta_{ctj,-\{1,k\}}^{g}\right) - \left(\mu_{jk} + \tau_{ctjk}^{g}\right)}{\sigma_{jk}} \right) } \right),$$

with $a_{ck}(.)$ the lower, and $b_{ck}(.)$ the upper truncation points for θ_{cjk} respectively. Using ϑ_{cjk} results in the following posteriors.

$\mu_{j0}\,|\,..\sim N\left(Q_{j0}\left(\Sigma_j^{-1}\left(\sum_{c=1}^{C}\widetilde{\vartheta_{ctj0}}\right)+H_{jg}^{-1}\eta_{jg}\right),Q_{j0}\right)$, and

$\tau_j^g\,|\,..\sim N\left(Q_{jg}\left(\Sigma_j^{-1}\left(\sum_{c=1}^{C}\widetilde{\vartheta_{ctjg}}\right)+H_{jg}^{-1}\eta_{jg}\right),Q_{jg}\right)$, where $Q_{j0}=\left(C\cdot T\cdot\Sigma_j^{-1}+H_j^{-1}\right)^{-1}$,

and $Q_{jg}=\left(\left(C_g+C_G\right)\cdot\Sigma_j^{-1}+H_j^{-1}\right)^{-1}$, with C_g the number of consumers assigned to search task g. further, $\widetilde{\vartheta_{ctj0}}=\begin{cases}\vartheta_{ctj}^g-\tau_j^g-\left(\sum_{r=1,r\neq 4}^{R}\upsilon_{j.r}^g w_{ctr}+\upsilon_{j.4}\theta_{c,t-1,j.}^{g`}\right) & \text{if } g_{ct}<G\\ \vartheta_{ctj}^G+\sum_{g=1}^{G-1}\tau_j^g-\left(\sum_{r=1,r\neq 4}^{R}\upsilon_{j.r}^G w_{ctr}+\upsilon_{j.4}\theta_{c,t-1,j.k}^{G`}\right) & \text{if } g_{ct}=G\end{cases}$,

and $\widetilde{\vartheta_{ctjg}}=\begin{cases}0 & \text{if } g_{ct}\notin\{g,G\}\\ \vartheta_{ctj}^g-\mu_j-\left(\sum_{r=1,r\neq 4}^{R}\upsilon_{j.r}^g w_{ctr}+\upsilon_{j.4}\theta_{c,t-1,j.}^{g`}\right) & \text{if } g_{ct}=g\\ -\left(\vartheta_{ctj}^g-\mu_j+\sum_{g'=1,g'\neq g}^{G-1}\tau_j^{g'}-\left(\sum_{r=1,r\neq 4}^{R}\upsilon_{j.r}^g w_{ctr}+\upsilon_{j.4}\theta_{c,t-1,j.}^{g`}\right)\right) & \text{if } g_{ct}=G\end{cases}$.

4. Using the transformed variables ϑ_{ctjk}^g , we can also draw υ_{jkr}^g ($r\neq 4$) and υ_{jk4} . First we correct for the overall bottom-up and top-down effects, by generating $\widetilde{\vartheta_{ctjk}^g}=\begin{cases}\vartheta_{ctjk}^g-\mu_{jk}-\tau_{jk}^g & \text{if } g<G\\ \vartheta_{ctjk}^g-\mu_{jk}+\sum_{g=1}^{G-1}\tau_{jk}^g & \text{if } g=G\end{cases}$. Further we define the matrix $W=\left[w_{ct1}^{g=1},..,w_{ctR}^{g=1},w_{ct1}^{g=2},..,w_{ctR}^{g=2},\theta_{c,t-1,jk}^g\right]$ with explanatory variables (in this case $G=2$, but this can be easily extended for more than two groups). Note that $\theta_{c,t-1,jk}^g$ is not defined for $t=1$, in this case $\theta_{c,t-1,jk}^g=0$. Further when consumer c in task $t=1$ searches for target g', we set $w_{ctr}^{g\neq g'}=0$ for all $r\in R$. This results in the following posterior distribution for $\Upsilon_{jk}=\left[\upsilon_{jk1}^{g=1},..,\upsilon_{jkR}^{g=1},\upsilon_{jk1}^{g=2},..,\upsilon_{jkR}^{g=2},\upsilon_4\right]$. $\Upsilon_{jk}\sim N\left(Q_k^\alpha\left(\Sigma_{jkk}^{-1}\cdot W'\widetilde{\vartheta_{.tjk}^g}+H_{jkk}^{\gamma}{}^{-1}a_k^\gamma\right),Q_k^\gamma\right)$, with $Q_k^\gamma=\left(\Sigma_{jkk}^{-1}\cdot W'W+H_{jkk}^{\gamma}{}^{-1}\right)^{-1}$.

5. $\Sigma_j^{-1}\,|\,..\sim W\left(\sum_{c=1}^{C}\left(\vartheta_{cj}-\left(\mu_j+\tau_{cjt}^g\right)\right)\left(\vartheta_{cj}-\left(\mu_j+\tau_{cjt}^g\right)\right)'+D_j^{-1},C+d_j\right)$

6. $$\Pi \mid .. \sim D\begin{pmatrix} \xi_{11} + \sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{i=2}^{n_{ct}} I\{z_{cti-1}=1\}\cdot I\{z_{cti}=1\} & \xi_{12} + \sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{i=2}^{n_{ct}} I\{z_{cti-1}=1\}\cdot I\{z_{cti}=2\} \\ \xi_{21} + \sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{i=2}^{n_{ct}} I\{z_{cti-1}=2\}\cdot I\{z_{cti}=1\} & \xi_{22} + \sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{i=2}^{n_{ct}} I\{z_{cti-1}=2\}\cdot I\{z_{cti}=2\} \end{pmatrix}$$

7. For the search performance parameters for each target g β^g_{time} and β^g_{acc} we apply the method of Chib and Greenberg (1998) to estimate multivariate probit models, and therefore allow estimating restricted covariance matrices. We first generate the latent variables V as follows:

$$V_c^g \mid .. \sim \begin{cases} TN_{>0}\left(F^g\beta^g_{acc} + \dfrac{\sigma_{12}^{perf,g}}{\sigma_{11}^{perf,g}}\left(y^g_{time} - F^g\beta^g_{time}\right), \left(1 - \dfrac{\left(\sigma_{12}^{perf,g}\right)^2}{\sigma_{11}^{perf,g}}\right)^{1/2}\right) & \text{if } y^g_{acc,c} = 1 \\ TN_{<0}\left(F^g\beta^g_{acc} + \dfrac{\sigma_{12}^{perf,g}}{\sigma_{11}^{perf,g}}\left(y^g_{time} - F^g\beta^g_{time}\right), \left(1 - \dfrac{\left(\sigma_{12}^{perf,g}\right)^2}{\sigma_{11}^{perf,g}}\right)^{1/2}\right) & \text{if } y^g_{acc,c} = 0 \end{cases},$$

with $F = \left[1\ f_1\left(\theta^g, z\right)\ f_2\left(\theta^g, z\right)\right]$, representing the constant, salience on the target, and the number of fixations on the target in the identification state. Using these latent variables V, we compute β^g_{time} and β^g_{acc} as follows:

$\begin{pmatrix} \beta^g_{time} \\ \beta^g_{acc} \end{pmatrix} \sim N\left(Q^g_{perf}\left(\left(I_2 \otimes F^g\right)'\left(\left(\Sigma^g_{perf}\right)^{-1} \otimes I_C\right)\begin{pmatrix} y^g_{time} \\ V^g \end{pmatrix} + \left(B^g_{perf}\right)^{-1} b^g_{perf}\right), Q^g_{perf}\right)$, with $Q^g_{perf} = \left(\left(I_2 \otimes F^g\right)'\left(\left(\Sigma^g_{perf}\right)^{-1} \otimes I_C\right)\left(I_2 \otimes F^g\right) + \left(B^g_{perf}\right)^{-1}\right)^{-1}$. Because the prior and the likelihood are not conjugate, we use a Metropolis-Hastings step to generate Σ^g_{perf}, as proposed by Chib and Greenberg (1998).

8. We are also interested in whether specific consumer characteristics $w^{id,g}$ influence the number of identification fixations on the target brand, computed as $\zeta^g_{ct} = \sum_{i=1}^{n_{ct}}\left(I\{z_{cti}=2\}\cdot\left(\sum_{d\in D_{\text{target}}} S^D_{ct}\left(a_{cti}, b_{cti}, d\right)\right)\right)$, where g is the target of task t. This results in the following posterior draws for ζ^g, and $\sigma^{id,g}$ respectively: $\zeta^g \mid .. \sim N\left(Q_{id}\left(\sigma^{-2}_{id,g}\cdot W^g_{id}{}' ID^g + H^{g-1}_{id} a^g_{id}\right), Q^g_{id}\right)$, with $Q_{id} = \left(\sigma^{-2}_{id}\cdot F'F + H^{g-1}_{id}\right)^{-1}$

$\sigma_{id,g}^{-2} \mid .. \sim G\left(\frac{C_g}{2} + d_0^{id,g}, \frac{2}{\left(ID^g - W_{id}^g{}'\zeta^g \right)^2} + D_0^{id,g} \right)$, with ID^g the vector containing the values of $\zeta_{c.}^g$ for all consumers searching for target g, and W_{id}^g the matrix with $w^{id,g}$ for all consumers.

9. Since we are interested in the fact whether the consumer characteristics W in step 4 have an effect on salience (via the different top-down weights), we project these variables on the salience of the target in the following way:
   $\upsilon_{saliency}^g = \left(W_g{}'W_g \right)^{-1} W_g{}'Y_{sal}^g$, with Y_{sal}^g the vector containing the saliencies of target g for all consumers.

To estimate the model, we use the same uninformative prior specification as in Chapter 3. The new priors, not included in the original brand search model are defined as follows: $\gamma_{jk}^g \sim N\left(a_k^{\gamma}, H_{jkk}^{\gamma\ -1} \right)$, $\gamma_{id}^g \sim N\left(a_{id}^g, H_{id}^{g-1} \right)$, and $\sigma_{id,g}^{-2} \sim G\left(d_0^{id,g}, D_0^{id,g} \right)$, with $\gamma_{jk}^g = \gamma_{id}^g = \mathbf{0}$, $H_{jkk}^{\gamma\ -1} = H_{id}^{g-1} = 10^4$, $d_0^{id,g} = R+1$ (note that number of identification fixations on target does not include across-trial priming), and $D_0^{id,g} = 10 \cdot I_{R-1}$.

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Nederlandse Samenvatting

Een noodzakelijke voorwaarde voor een merk om in het boodschappenmandje van de consument te belanden is dat dit merk gevonden wordt tussen de andere producten in het schap. Het voldoen aan deze voorwaarde is een steeds grotere uitdaging voor winkeliers en fabrikanten. Dit komt doordat gehaaste klanten steeds minder tijd aan winkelen willen besteden en doordat er steeds meer verschillende producten in dezelfde categorie worden aangeboden. Bovendien lijken de verpakkingen van deze verschillende producten erg veel op elkaar door categoriecodes en de introductie van steeds meer namaakverpakkingen. Recent onderzoek in verschillende supermarkten heeft aangetoond dat de verkopen van een merk kunnen verdubbelen wanneer dit merk meer opvalt, en dus gemakkelijker gevonden wordt in het schap. Dit heeft ertoe geleid dat fabrikanten steeds meer investeren in de vormgeving van verpakkingen, zodat de producten beter opvallen en makkelijker gevonden kunnen worden. Kellogg's [1] heeft bijvoorbeeld onlangs al haar verpakkingen van ontbijtgranen aangepast, omdat consumenten verward raakten door de vele op elkaar lijkende verpakkingen.

Hoewel onderzoek heeft aangetoond dat producten die snel gevonden worden ook meer verkocht worden, is het opvallend dat er nog geen onderzoek gedaan is naar de vraag hoe consumenten een product vinden in een schap. Deze vraag staat centraal in dit proefschrift. Om deze vraag te beantwoorden zijn in dit proefschrift drie onderzoeken uitgevoerd, die achtereenvolgens in de volgende paragrafen van deze samenvatting beschreven zullen worden. Het eerste onderzoek (hoofdstuk 2) introduceert een nieuw conceptueel model die het zoekgedrag van consumenten beschrijft. Dit conceptuele model wordt vervolgens empirisch getoetst met behulp van

[1] Kellogg's persbericht, juli 2002: "Nieuw ontwerp onderscheidt Kellogg's van de rest" www.kelloggs.nl/informatie/1_02.html

oogbewegingsdata van consumenten. Het tweede onderzoek (hoofdstuk 3) richt zich op opvallendheid van verpakkingen, een factor die een belangrijke rol speelt in het zoekproces en die met behulp van het model uit het eerste onderzoek afgeleid kan worden. Het laatste onderzoek (hoofdstuk 4) gaat in op leereffecten tijdens zoektaken, en bestudeert of consumenten die voor de tweede keer op hetzelfde schap naar een product zoeken efficiënter zijn en waarom. Deze samenvatting wordt afgesloten met een korte conclusie.

Analyse van Oogbewegingen tijdens Zoektaken (Hoofdstuk 2)

Beschrijving conceptueel model van het zoekproces

Tijdens iedere zoektaak moeten de volgende twee problemen opgelost worden: 1) een *locatieprobleem*: waar staat het merk in het schap?, en 2) een *identificatieprobleem*: is het gelokaliseerde product het merk dat we zoeken, of is het een ander merk? Het opsplitsen van een zoektaak in deze twee deelproblemen zorgt ervoor dat de complexiteit van de taak aanzienlijk kleiner wordt. Verder is er sterk bewijs uit de neuropsychologie dat deze twee deelproblemen door twee verschillende visuele banen in de hersenen worden opgelost: de dorsale baan en de ventrale baan. De dorsale baan is belast met het lokaliseren van een object, terwijl de ventrale baan zich bezig houdt met object identificatie. Gedurende een zoektaak wisselt de aandacht van een consument dus tussen twee latente fasen: een locatiefase om het locatieprobleem op te lossen, en een identificatiefase om het identificatieprobleem op te lossen.

Tijdens de locatiefase kunnen consumenten twee strategieën gebruiken: een strategie gebaseerd op opvallendheid, en een systematische strategie. De strategie gebaseerd op opvallendheid richt zich op de visuele kenmerken van het te zoeken merk, zoals kleur, helderheid en vorm. De aandacht van consumenten in deze strategie wordt gericht op plaatsen in het schap die overeenkomen met kenmerken van het te zoeken merk, zoals deze opgeslagen zijn in het geheugen van de consument. Deze strategie kan dus efficiënt zijn wanneer de consument deze visuele eigenschappen kent, en wanneer deze eigenschappen diagnostisch zijn voor het te zoeken merk. Een consument die bijvoorbeeld naar Douwe Egberts koffie zoekt, kan zich bijvoorbeeld herinneren dat de verpakking van dit product rood is. Deze kleur is echter niet diagnostisch, aangezien veel verpakkingen in deze categorie de kleur rood bevatten. Naast deze strategie gebaseerd op opvallendheid, kan een consument ook een systematische strategie gebruiken die gebaseerd is op de structuur van het schap.

Tijdens deze strategie scant de consument op een geordende manier de verpakkingen in het schap. Een voorbeeld van zo'n strategie is een leesstrategie, waarin consumenten van links naar rechts systematisch de verpakkingen analyseren.

In de andere fase, de identificatiefase, richten consumenten de aandacht op specifieke kenmerken van een verpakking, zoals merknaam en logo. In dit geval zal de aandacht gefocust blijven op een geselecteerd merk in de locatiefase.

Analyseren van het zoekproces: Oogbewegingsdata

Dit proefschrift maakt gebruik van oogbewegingsdata om het zoekproces te meten. Oogbewegingen kunnen onderverdeeld worden in twee belangrijke componenten: fixaties en saccades. Fixaties zijn korte periodes (ongeveer 250 ms) waarin het oog relatief onbewegelijk is. Tijdens deze korte periodes wordt informatie opgenomen van de omgeving rondom de gefixeerde locatie. Saccades zijn sprongen van het oog tussen twee fixatiepunten. Gedurende deze sprongen (ongeveer 30 ms) wordt geen informatie opgenomen.

Hoewel oogbewegingen de meeste gedetailleerde gegevens zijn om het zoekproces te meten, worden deze data maar beperkt gebruikt in onderzoek naar zoekgedrag. De reden hiervoor is dat oogbewegingsdata erg complex zijn, en dat er nauwelijks statistische modellen ontwikkeld zijn om deze gegevens te analyseren. In hoofdstuk 2 wordt daarom een ruimtelijk statistisch model ontwikkeld die de oogbewegingen analyseert van consumenten tijdens zoekprocessen. Het model, dat gebaseerd is op het conceptuele model van het zoekproces, gebruikt de ruimtelijke coördinaten van de oogfixaties om dit proces af te leiden. Het ontwikkelde statistische model houdt rekening met heterogeniteit tussen consumenten en bevat een Hidden Markov Component die de fixaties indeelt in locatie- en identificatiefixaties. Verder leidt het model het belang van verschillende verpakkingselementen af (zoals kleuren, en vorm), terwijl het model controleert voor de systematische zoekstrategieën.

Resultaten toepassing

Het ontwikkelde model is gebruikt om de oogbewegingen van consumenten te analyseren die gedurende een experiment zochten naar Van Nelle koffie tussen 11 andere koffiemerken. Het ontwikkelde model blijkt zeer geschikt te zijn om het onderliggende zoekproces te achterhalen. Het model geeft duidelijk aan dat consumenten regelmatig wisselen tussen de twee latente fasen, en achterhaalt welke verpakkingselementen een belangrijke rol spelen in het zoekproces. Validatie analyses laten verder zien dat de consumentspecifieke parameterschattingen een significante relatie hebben met zoektijd en nauwkeurigheid. Zoals verwacht zijn consumenten die op de juiste diagnostische eigenschappen van een merk zoeken nauwkeuriger en vinden zijn het merk bovendien ook sneller.

Opvallendheid van Verpakkingen in Zoektaken (Hoofdstuk 3)

Zoals hoofdstuk 2 beschrijft, speelt de opvallendheid van verpakkingen een belangrijke rol tijdens het zoekproces naar merken. Merken die meer opvallen worden eerder gevonden, en zullen daardoor een grotere kans hebben om gekocht te worden. Met behulp van het model ontwikkeld in hoofdstuk 2 zijn we in staat de opvallendheid van verpakkingen af te leiden. Opvallendheid bestaat echter uit twee belangrijke componenten: een exogene en een endogene component. De exogene component hangt volledig af van de verpakkingen op het schap en is voor iedere consument gelijk, bijvoorbeeld een pak Pringles chips valt op tussen zakken chips. De endogene component is consument specifiek en hangt af van de zoektaak (welk merk wil de consument vinden) en de kenmerken van het gezochte merk zoals deze zijn opgeslagen in het geheugen van de consument. Wanneer een consument bijvoorbeeld op zoek is naar een zak Lay’s paprika chips, dan zal de consument zijn aandacht kunnen richten op blauwe zakken chips, en hierdoor zullen de pakken Pringles minder opvallend zijn. Voor marketing managers is het erg belangrijk om de exogene en endogene component van opvallendheid te achterhalen, aangezien beide componenten met behulp van verschillende marketing instrumenten beinvloed kunnen worden. De exogene component wordt voornamelijk beinvloed door het ontwerp van de verpakking en de positie in het schap, terwijl de endogene component beinvloed kan worden door bijvoorbeeld advertenties.

Dit hoofdstuk breidt het model van hoofdstuk 2 uit zodat beide componenten van opvallendheid: exogeen en endogeen, per merk afgeleid worden. Naast deze uitbreiding relateren we de consumentspecifieke zoekparameters direct aan zoekprestatie: snelheid en nauwkeurigheid. De twee componenten kunnen worden onderscheiden doordat we verschillende consumenten naar verschillende producten op een schap laten zoeken. Het ontwikkelde model is toegepast op de oogbewegingsdata van consumenten die zochten naar één van vijf verschillende wasmiddelen op een schap met 16 concurrerende merken.

De resultaten in dit hoofdstuk laten duidelijk zien dat beide componenten: exogeen en endogeen, een belangrijke rol spelen in de opvallendheid van verpakkingen. Hoewel een aantal specifieke verpakkingselementen aandacht trekken onafhankelijk van de zoektaak (de exogene component), hangen de gewichten van deze elementen sterk af van het doel van de consument (de endogene component). Een opmerkelijk resultaat is dat consumenten per doel de opvallendheid van slechts één kenmerk kunnen versterken. Bijvoorbeeld, wanneer een consument naar Persil zoekt wordt het gewicht van de kleur groen endogeen versterkt, terwijl de gewichten van de overige kleuren gelijk blijven of verminderen. Naast het feit dat we de endogene gewichten van specifieke verpakkingselementen af kunnen leiden, geeft het model ook aan wat de consequenties zijn voor de opvallendheid van andere merken op het schap. Immers, wanneer een merk wint aan opvallendheid, moet dit ten koste gaan van de opvallendheid van een of enkele andere merken. Een interessante bevinding is dat de ‘strijd om opvallendheid’ asymmetrisch is. Dit betekent dat wanneer merk A aan opvallendheid wint ten koste van merk B, het niet noodzakelijk zo hoeft te zijn dat merk A aan opvallendheid verliest wanneer een consument naar merk B zoekt. Deze competitieve opvallendheids analyse levert belangrijke resultaten op die gebruikt zouden kunnen worden in de optimalisatie van verpakkingen.

Geheugeneffecten tijdens Herhaaldelijk Zoeken (Hoofdstuk 4)

In de twee voorgaande hoofdstukken zochten consumenten slechts eenmaal in een schap dat ze voor het eerst zagen. In de praktijk zoeken consumenten echter regelmatig in een schap dat ze al eerder gezien hebben tijdens voorgaande bezoeken aan dezelfde winkel. Het is echter onbekend of en welke informatie uit eerdere zoektaken gebruikt wordt door consumenten, en hoe deze informatie het zoekproces beïnvloedt. Om dit te analyseren hebben we de oogbewegingen van consumenten geanalyseerd die tweemaal naar een pak koffie zochten in hetzelfde schap. De ene helft consumenten zocht eerst naar Douwe Egberts koffie, en daarna naar Van Nelle koffie, voor de andere helft consumenten was de volgorde precies andersom.

Uit het onderzoek in dit hoofdstuk blijkt dat consumenten inderdaad informatie uit een eerdere zoektaak op hetzelfde schap gebruiken. Deze informatie wordt voornamelijk gebruikt in de locatiefase van de tweede taak, en niet in de identificatiefase. Een interessante bevinding in dit onderzoek is dat wanneer consumenten in de tweede taak naar een merk zoeken die ze in de eerste taak gezien hebben, ze in staat zijn de opvallendheid van dit merk te vergroten. Deze toename in opvallendheid heeft vervolgens weer een positief effect op de zoekprestatie gemeten in zoektijd en nauwkeurigheid. Dit betekent dat consumenten tijdens zoektaken informatie over verpakkingen opslaan waar zij niet naar op zoek zijn, en dit gebeurt in enkele fracties van seconden. Dit resultaat onderstreept de adverterende rol die verpakkingen kunnen vervullen, en geeft het belang aan voor merken om in het schap te staan, ook voor consumenten die niet op zoek zijn naar het product. Deze adverterende rol zou daarom een additionele verklaring kunnen zijn voor de hoge bedragen die fabrikanten tegenwoordig moeten betalen om hun nieuwe producten in het schap van een winkelier te mogen plaatsen.

Conclusie

In dit proefschrift heb ik met behulp van oogbewegingsgegevens onderzocht hoe consumenten een product vinden in een schap. Deze gegevens, in combinatie met het nieuw ontwikkelde statistische model, hebben nieuwe inzichten opgeleverd over het zoekproces naar merken. De resultaten zijn relevant voor het ontwerpen van verpakkingen, het organiseren van schappen, en het achterhalen van andere factoren, zoals commercials, die het zoekproces kunnen beïnvloeden. Het ontwikkelde statistische model is geschikt om oogbewegingen op een gedetailleerde manier te analyseren, en is daardoor ook geschikt om de aandachtsprocessen in andere contexten, zoals advertenties, commercials en het internet te onderzoeken. De ontwikkeling van oogbewegingsregistratie is nog steeds in volle gang, en de meetapparatuur wordt steeds goedkoper en geschikter voor grootschalig consumentenonderzoek. Ik hoop dat dit proefschrift daarom zal bijdragen aan meer onderzoek naar aandachtsprocessen van consumenten, zodat winkeliers en fabrikanten betere richtlijnen hebben die ervoor zorgen dat wij, consumenten, gemakkelijker onze producten kunnen vinden.