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Consumer behavior at the point of purchase is influenced by out-of-store memory-based factors (e.g., brand preferences) and by in-store attention-based factors (e.g., shelf position and number of facings). In today's cluttered retail environments, creating memory-based consumer pull is not enough; marketers must also create "visual lift" for their brands—that is, incremental consideration caused by in-store visual attention. The problem is that it is currently impossible to precisely measure visual lift. Surveys can easily be conducted to compare pre-store intentions and post-store choices but they do not measure attention. They cannot therefore tell whether ineffective in-store marketing was due to a poor attention-getting ability—"unseen and hence unsold"—or to a poor visual lift—"seen yet still unsold".

Eye-tracking studies have shown that eye-movements to brands displayed on a supermarket shelf are valid measures of visual attention and are generally correlated with brand consideration (Pieters and Warlop 1999; Russo and Leclerc 1994). However, they have not provided a method for separating the effects of attention and memory on consumer point-of-purchase decisions. More specifically, they have not shown that attention to a brand causes consideration, rather than memory for a considered brand causing visual search for that brand.

In this chapter, we show how commercially-available eye-tracking data can be used to decompose a brand's consideration into its memory-based baseline and its visual lift. To achieve this goal, we develop a parsimonious decision-path model of visual attention and brand consideration. We apply this model to eye-movements and brand consideration data collected by Perception Research Inc., the leading US provider of eye-tracking studies for marketing research. Our results confirm the importance of visual-based factors in driving brand consideration using a richer and more realistic setting than in existing studies. The two studies also provide new insight into consumer's decision-making process at the point of purchase, and particularly on the interplay between consideration decisions and visual attention to prices and packages. Finally, we show how the decomposition can help decide which brands of a shelf display should be selected for enhanced P-O-P marketing activities.

In the first section of the chapter, we present a framework for the effects of memory and attention at the point of purchase and review the data and methods available to measure these effects. In the second section, we describe the procedure, stimuli, and key descriptive findings of two studies that measured the eye movements and consideration decisions of consumers while they were looking at supermarket shelf displays. In the third section, we introduce a decision-path model of visual attention and consideration decisions and show how this model can be applied to estimate a brand's visual lift and visual responsiveness. There have been significant advances in the modeling of eye-tracking data in recent years (e.g., Pieters, Warlop, and Wedel 2002; Pieters and Wedel 2004; Wedel and Pieters 2000). These studies have developed integrative models of the antecedents and consequences of visual attention to sections of print ads. In the research reported here, we have placed emphasis on parsimony and managerial relevance and have restricted our analysis to the type of data routinely collected by eye-tracking providers (i.e., observational rather than experimental data). In the final section, we discuss how retailers and manufacturers can use the results of estimating the decision-path model to better assess the visual display of brands at the point of purchase.

CONCEPTS AND MEASURES OF POINT-OF-PURCHASE MARKETING

According to the Point of Purchase Advertising Institute, 74 percent of all purchase decisions in mass merchandisers are made in store (POPAI 1997). Yet consumers only look at and evaluate a fraction of the hundreds of alternatives cluttering supermarket shelves (Inman and Winer 1998 ; Kollat and Willett 1967). In these conditions, it is not surprising that attracting consumers' visual attention at the point of purchase strongly influences consumer choices. For example, Woodside and Waddle (1975) showed that P-O-P signing multiplies the effects of a price reduction by a factor of six and that it can even increase sales in the absence of price change (see also Bemmaor and Mouchoux 1991). Other field experiments have documented the influence of shelf space, location quality, and display organization on sales (e.g. Drèze, Hoch, and Purk 1994; Wilkinson, Mason, and Paksoy 1982).

The Effects of Memory and Visual Attention at the Point of Purchase

One way to categorize the sources of marketing effects at the point of purchase is to distinguish between memory-based and visual-based[1] effects (Alba, Hutchinson, and Lynch 1991). As summarized in Figure 1, any observed behavior at the point of purchase (e.g., brand consideration or choice) is influenced by both memory-based and visual factors and, in principle, can be decomposed into a baseline memory-based response and an incremental visual lift. We define memory-based response as the part of consumer behavior attributable to factors residing in memory, such as brand preferences. We define visual lift as the part of consumer behavior attributable to factors mediated by visual attention, such as shelf location, number of facings, and price displays. As indicated in Figure 1, these factors are predominantly under the control of the retailer. In comparison, manufacturers typically devote more resources to and exert greater influence upon the factors influencing memory-based response.

--- Insert Figure 1 here ---

In this research, we measure and model brand consideration rather than brand evaluation or choice because it is more sensitive to visual attention effects than choice, which

[1] Usually, the more general term "stimulus-based" is used. However, at the point of purchase the perceptual stimuli are almost exclusively visual in nature and given our focus on visual attention we use the more specific term throughout.

is likely to be mostly driven by memory-based factors. Also, consideration is directly relevant for manufacturers because most of the variance in final brand choice is driven by inclusion in the consideration set (Hauser and Wernerfelt 1990) and for retailers because a larger consideration set increases the chances that consumers will make at least one purchase from the category. We operationally define memory-based response as the probability of inclusion in the consideration set when the decision is made purely from memory, and visual lift as the incremental consideration gained from noticing the brand at the point of purchase.

Traditional Methods for Measuring Visual Lift

Most market research methods are not appropriate because they focus on evaluation or choice once the alternatives being evaluated have captured consumer's attention. One exception are field experiments, which measure a brand's visual lift by manipulating its visual salience (the likelihood that it will attract in-store attention) and measuring its impact on sales or consumer shopping behavior (for a review, see Blattberg and Neslin 1990). Even though field experiments can now be more easily implemented via computerized simulations (e.g., Burke et al. 1992), they remain time consuming and costly. Also, by measuring only incremental effects (i.e., one P-O-P condition compared to another) these measures leave unanswered the question of the relative contributions of memory and visual attention to observed rates of consideration and choice.

Another exception are in-store surveys. Compared to field experiments, they do not necessitate the experimental manipulation of visual salience and measure visual lift at the individual level by comparing pre-store purchase intentions or memory-based consideration with post-store brand choices or post-hoc recollection of in-store brand consideration (e.g., Hoyer 1984; Inman and Winer 1998). However, in-store surveys have several shortcomings.

Because they do not have information on visual attention, they cannot tell whether a small difference between pre-and post-store choice is really due to low visual lift (i.e., in-store attention does not increase choice much) or simply to low attention to the brand. Second, visual attention to a brand can trigger the memory-based consideration of other brands (Hutchinson, Raman, and Mantrala 1994). Because they are purely memory-based, surveys miss this type of stimulus-based consideration and thus may overestimate visual lift. Third, pre-store intentions can be influenced by social desirability biases and measuring them before people enter the store can lead to purchases that would not have occurred otherwise (Chandon, Morwitz, and Reinartz 2005).

Eye-Tracking Studies

Eye-tracking studies provide direct measures of eye movements in a realistic stimulus-based setting and do not require verbalizing pre-store memory-based consideration. Eye movements consist of fixations, during which the eye remains relatively still for about 200-300 milliseconds, separated by rapid movements, called saccades, which average 3-5° in distance (measured in degrees of visual angle) and last 40 to 50 milliseconds (for more information, see Rayner's chapter in this volume). Eye-tracking equipment records the duration of each eye fixation and the exact coordinates of the fovea (the central 2° of vision of the visual field) during the fixation with a frequency of 60 readings per second (i.e., one every 17 milliseconds). It then maps the coordinates of the fovea to the location of each area of interest on the picture (e.g., individual brands on a supermarket shelf picture).

Eye-tracking studies are a niche, but fast-growing, segment of the P-O-P market research industry. They are the method of choice for commercial studies of package design and shelf displays (Young 2000). Commercial eye-tracking studies typically focus on the percentage of subjects “noting” the product (i.e., making at least one eye fixation on the product). More recently, commercial eye-tracking studies have started instructing consumers to imagine that they need to buy from the category and have collected brand consideration data as well as eye-movement data.

Consumer researchers have used eye-tracking data to study how people look at print advertisements (e.g., Pieters and Wedel 2004; Wedel and Pieters 2000), yellow pages (Lohse 1997), and catalogues (Janiszewski 1998). These studies have shown that eye-tracking data provide reliable measures of attention to stimuli in complex scenes, such as brands on a supermarket shelf (Hoffman 1998; Lohse and Johnson 1996; Rayner 1998). Although attention can be directed without eye movements to stimuli located outside the fovea (the central 2° of vision), the location of the fovea during the eye fixation is a good indicator of attention to complex stimuli because little complex information can be extracted during saccades, because foveal attention is more efficient than parafoveal attention, and because visual acuity deteriorates rapidly outside the fovea.

Two previous studies have specifically demonstrated the value of eye-tracking data for measuring visual attention to products displayed on supermarket shelves. Russo and Leclerc (1994) isolated the sequences of consecutive eye fixations revealing brand comparisons using a method developed earlier (Russo and Rosen 1975). These sequences of eye fixations revealed that consumers making in-store purchase decisions go through three stages: orientation, evaluation, and verification. Pieters and Warlop (1999) examined the effect of time pressure and task motivation on visual attention to the pictorial and textual areas of products displayed on supermarket shelves. They showed that subjects respond to time pressure by making shorter eye fixations and by focusing their attention on pictorial information. In addition, both studies showed that consideration increases with the number of eye fixations to the brand.

Still, existing studies of eye movements to supermarket shelves have some limitations. First, they do not provide a method for separating the effects of memory-based factors from those of attention-based factors, leaving open the question “Is unseen really unsold?” Second, these studies do not provide much guidance for the allocation of P-O-P marketing activities between the brands of the display. Finally, it is useful to test the robustness of the descriptive findings of these two studies, as they were obtained for relatively simple displays (only one facing per brand, brands well separated from each other, and no price information) and either few brands (six for Pieters and Warlop 1999) or early eye movement recording techniques (manual coding of eye fixations from videotapes for Russo and Leclerc 1994). In the next sections, we present the procedure, stimuli, and key descriptive findings of our studies involving eye-tracking and brand consideration data generated by consumers looking at realistically rich shelf displays in two product categories. We then show how a decision-path model calibrated on these data can be used to estimate memory-based consideration and visual lift and thereby accomplish our goals.

TWO EYE-TRACKING STUDIES

Procedure and Stimuli

The data used in our analyses were collected in collaboration with Perception Research Services, Inc. (PRS) of Fort Lee, NJ, following the procedure and stimuli typically used in commercial tests of package designs. Adult shoppers were recruited in shopping centers in eight US cities and offered $10 for their participation. They were female heads of household responsible for the majority of their household's grocery shopping. Their ages ranged from 24 to 65, they had at least a high-school education, and earned a minimum annual household income of $25,000. The final group of respondents included a mix of full-time working people, part-time working people and full-time homemakers. A total of 309 consumers were recruited, split between the two product categories studied (159 for orange juices, 150 for liquid detergents).

Each person was seated and told that she would see a series of ads like those found in magazines or a series of products like those found in stores. They went through a calibration procedure requiring them to look twice at a blank 35mm slide with five circles projected on a 4 x 5 feet screen located approximately 80 inches away from the seat. Thus, the 2 degrees of foveal vision covered about 3 inches on the screen. This was less than one shelf facing (which was 3.3 inches for juices and 6 inches for detergents), indicating that consumers could not extract detailed information from different brands from a single eye fixation. Their eye movements were tracked using infrared corneal reflection (ISCAN model #AA-UPG-421), which does not require headgear. Subjects then looked at four or five training displays and at six pictures of individual packages or print ads for an unrelated study. For this unrelated study, subjects were only asked to look at the pictures as they would normally do.

Prior to viewing the last stimulus (i.e., the one used in our studies), subjects were instructed that they would have to say which brands they would consider buying among those shown in the display. The names of the brands considered were recorded during the eye-tracking task by PRS staff as respondents verbalized them. Subjects controlled the amount of time spent looking at the display by pressing a button to go to the following slide (and this time was automatically recorded). After the eye-tracking task, subjects went to a separate room where PRS staff measured brand recall, past brand usage and general questions about shopping behavior in the product category. Each interview lasted approximately 20-25 minutes, of which 5 to 10 minutes were spent in the eye-tracking room.

--- Insert Table 1 and Figures 2 and 3 here ---

The stimuli were two pictures of supermarket shelves used by PRS in prior studies, one representing orange juices and the other liquid laundry detergents. The two product categories were chosen because of their high level of household penetration (87 % for fruit juices and 80% for liquid laundry detergent) and high percentage of sales sold on P-O-P display (respectively, 11% and 25% in 1998, according to Information Resources). The two categories, however, differed on a number of important variables related to visual display and consumer behavior. The picture of orange juices consisted of 16 choice alternatives (which for simplicity we will call "brands" throughout the paper) displayed horizontally on four shelves with a total of 72 facings (see Figure 2). There were 10 brands of liquid laundry detergents, each displayed vertically on three shelves with a total of 30 facings (see Figure 3). The brands were defined so as to match the classification used in the verbal interviews, and they varied in their level of generality. For instance, Figure 2 shows that there are three different brands with the Tropicana umbrella brand name (Tropicana Pure Premium, Tropicana Season's Best and Tropicana Pure Tropic) because these three alternatives were coded as separate choices in the verbal interviews. In order to expand the range of memory-based and visual lift that would be observed, we created two fictitious brands, Jaffa for juices, and Clin for detergents. The packaging of these two brands were patterned after products sold outside the United States. Their price was determined during pre-tests to position these two brands as regional or store brands. In addition, up to four shelf-talkers displaying the brand's logo were added to some brands in some test locations. Because the effects of shelf talkers were small and not reliable across product categories, the data were aggregated across the four test locations for juices and the four test locations for detergents.

Detergent brands occupied slightly more shelf space, were priced higher (displayed prices were the regular prices for a food store chain in Philadelphia at the time of the experiment), and were bought less regularly than juice brands (see Table 1). In addition, consumers are generally more brand loyal and less likely to buy detergents on impulse (all differences are statistically significant). These differences between juices and detergents suggest that results holding across these two categories are relatively robust.

Descriptive Results

Table 1 reports the key results regarding visual attention and brand consideration for juices and detergents. Consumers spent more time looking at the juice display than at the detergents display (25.06 vs. 17.99 seconds, $F(1, 307) = 13.7$, $p < .001$). These numbers are comparable to the in-store observations reported for detergents by Hoyer (1984) in the US and by Leong (1993) in Singapore (respectively 13.2, $t = .51$, $p = .71$ and 12.2 seconds, $t = .62$, $p = .55$). This suggests that consumers were only slightly more involved in the eye-tracking study than in a real shopping situation.

Interestingly, consumers also noted (i.e., fixated at least once) more brands for juices (10.93 vs. 7.09 for detergents, $F_{1,307} = 132.5$, $p < .001$) but considered the same number of brands in both categories (2.57 brands for juices vs. 2.29 brands for detergents, $F_{1,307} = 1.6$, $p = .21$). The size of the consideration set for juices is comparable to the number (3.22, $t = .65$, $p = .72$) reported by Hauser and Wernerfelt (1990) for the same category (Hauser and Wernerfelt do not provide data on liquid laundry detergents). The percentages of participants considering each brand are given in Figures 2 and 3. Participants noted three to four times more brands than they considered, showing that noting is not a direct proxy for brand consideration. This also indicates that one needs to separately model visual attention and brand consideration if one wants to measure visual lift.

The visual area of each brand was separated into the price tag area and the package area. As shown in Table 1, consumers only looked at 4.0 price tags for juices and at 2.5 price tags for detergents. Virtually no brands were fixated on the price area alone, as indicated by the almost negligible increase between the number of packs noted and the number of brands (pack or price) noted (see Table 1). Other aspects of the data also demonstrated the predominance of packages in visual attention and generally low levels of price information processing (c.f. Dickson and Sawyer 1990). For example, consumers almost never noted a product's price if they had not already noted its pack, and when consumers looked at both the pack and the price of the same brand, the pack was noted 6.0 seconds earlier for juices and 4.7 seconds earlier for detergents. Drawing on these results, all subsequent analyses are based on data aggregated to the brand level (i.e., pack or price).

Although these results show important differences between juices and detergents, the overall picture shows surprisingly similar results when controlling for differences in the number of brands displayed in each category. The proportion of brands noted is very similar across both categories (68% for juices and 71% for detergent). It is also similar to the results reported by Russo and Leclerc (1994) for other categories (69% for ketchup, 61% for applesauce, and 60% for peanut butter). The number of fixations on packs and prices is also remarkably similar across both categories: in both categories, two thirds of packages are noted (66% for juices and 69% for detergents) and only one quarter of prices are noted (25% for both juices and detergents). Finally, most visual search involves transitions to a different brand rather than within-brand search (92% of observations for juices and 91% for detergents).

--- Insert Figure 4 here ---

Similarly, robust results were obtained when looking at the number of fixations on brands and the average consideration conditional on the number of fixations (see Figure 4). For both categories, brands are more likely to be either fixated at least twice (with probability .50 for juices and .55 for detergents) or never fixated (with probability .32 for juices and .29

for detergents) than of being fixated exactly once (with probability .18 for juices and .16 for detergents). Also, for both categories, there is a strong relationship between consideration and the number of eye fixations. On average, making at least two eye fixations added 13 percentage points to the probability of consideration for juices and 10 points for detergents compared to brands that were not fixated on at all. Finally, although infrequent (2.2% of observations for juices and 4.3% of observations for detergents), brands are sometimes included in the consideration set even though they were never fixated on. The most likely explanations of this are that some packages are so well known that only peripheral vision is required to identify their presence or that consumers assume their presence based on past experience alone. Further research will be required to address this issue. However, it is consistent with our framework and subsequent model, which postulate that consumers may have a purely memory-based probability of considering a brand before looking at it.

Overall, the descriptive results are largely consistent with in-store observations, supporting the face validity of eye-tracking studies. They show that consumer visual information processing at the point of purchase is limited and mostly driven by packages rather than by prices and that across-brands search is more common than within-brand search. They also provide evidence for both purely memory-based consideration (hence unseen is not always unsold) and for a positive relationship between the number of in-store eye fixations and brand consideration (brands fixated more are more likely to be considered). Of course, these results do not tell whether additional looks yield additional consideration or whether consumers look multiple times at brands that they have already decided to consider (or whether it is some combination of the two). We address this issue in the next section by developing a probability model that links visual attention and brand consideration in both ways.

A DECISION-PATH MODEL OF VISUAL ATTENTION AND CONSIDERATION AT THE POINT OF-PURCHASE

The main objective of the decision-path model is to separate the effects of visual factors from memory-based factors as a determinant of brand consideration. In particular, observed likelihoods of consideration for each level of eye fixation are used to estimate a base probability of consideration that is due to out-of-store decision making (i.e., memory-based response) and the incremental consideration probability due to in-store visual attention (i.e., visual lift). Our goal in developing our path dependent process model was to balance both parsimony and a behaviorally plausible parametric representation. We have thus placed great value on keeping the model simple, estimable using typical commercial eye-tracking data, and helpful and easy to use by managers. To our knowledge, this is the first model of this type in either the marketing or the psychological literatures, so prudence suggests simplicity. Also, the basic data (i.e., the joint frequencies of noting and considering) provide only 6 possible outcomes (i.e., df = 5) for each brand, so brand-level models must be parsimonious. Still, the model presented here provides a multi-stage decision process for fixation and consideration that is consistent with both the extant literature and our data. The computational approach taken here is general, and hence other tree-like path models can be fit and compared to the one presented here.

Model Specification

We model the P-O-P decision making process as a sequence of events that alternate between sub-decisions to consider the brand and sub-decisions to make an eye fixation on the brand (see Figure 5). The model assumes that consumers have a memory-based probability of consideration for each brand. This assumption is supported by studies showing that consumers have a long-term consideration set in memory (Shocker et al. 1991).

--- Insert Figure 5 here ---

The first decision is a memory-based, pre-store consideration that is made before any in-store visual information is assessed (i.e., before the brand is noticed). Next, consumers decide whether or not to look at the brand.[2] If the brand is not fixated, no new information is acquired, and the consideration decision remains unchanged. If the brand is fixated, the new eye fixation provides a new opportunity to consider the brand. We assume that consideration is irreversible; that is, having considered a brand, consumers might choose to look at it again but they do not “un-consider” it.

Figure 5 depicts the nine possible decision paths in the model and the outcomes that would be observed in our data. For brand j, α_j is the probability of making an eye fixation (its visual salience) and β_j is the probability of including the brand in the consideration set. In the simple version of the model depicted in Figure 5, β_j is the same whether the occasion of possible consideration is pre- or post-fixation. Our data allows us to discriminate between no fixations, one fixation, and two or more fixations. Therefore, we assume that if the brand is not in the memory-based consideration set (which happens with probability 1-β_j), then the first fixation provides a new opportunity to consider it with probability β_j. Similarly, if the brand is still not considered after the first fixation, subsequent fixations lead to consideration with probability β_j. Each decision path is mutually exclusive of the others and exhaustive of the possible sequences of events. The probability that a specific path occurs is computed as the product of its sub-decision probabilities. For example, the probability of being in the first

[2] As with most quantitative models of perceptual and cognitive processes, the represented process greatly simplifies the actual process. It captures certain aspects of decision making (e.g., the temporal flow of looking and consideration), but ignores others (e.g., whether the decisions to look and consider are conscious and deliberate, non-conscious and associative, or some mixture of the two).

path (i.e., no fixation and no consideration) is, p_{1j} = (1-β_j)*(1-α_j). The probabilities of the nine decision paths are given in Appendix A.

As can be seen in Figure 5, the overall predicted probability of consideration is the sum of the individual probabilities of taking one of the six decision paths leading to positive consideration (p_{4j} to p_{9j}). Predicted consideration can be expressed as a function of α_j and β_j, as follows:

$$c_j \quad = \quad \beta_j + \beta_j\, \alpha_j\, (1 - \beta_j) + \beta_j\, \alpha_j^2\, (1 - \beta_j)^2 \qquad (1)$$

Model Implications, Visual Lift, and Visual Responsiveness

One immediate implication of the model is that the conditional probability of consideration given fixation increases with the number of fixations (which is consistent with the results reported in Figure 4). It is easy to see from Equation 1 that the probability of considering the brand is the memory-based consideration probability, β_j (i.e., probability of paths 7, 8, or 9 occurring), plus the incremental consideration provided by the first eye fixation, $\beta_j\ \alpha_j\ (1 - \beta_j)$ (i.e., probability of paths 5 or 6 occurring), plus the incremental consideration provided by the second eye fixation, $\beta_j\ \alpha_j^2\ (1 - \beta_j)^2$ (i.e., probability of path 4 occurring). In other words, Equation 1 shows that each eye fixation provides a new chance to consider the brand (with probability β_j) provided that the brand is noted (with probability α_j for the first fixation and α_j^2 for the second fixation) and that previous consideration decisions were negative (with probability $(1 - \beta_j)$ for the first fixation and $(1 - \beta_j)^2$ for the second fixation).

A somewhat subtler prediction of the model is that the increase in the conditional probability of consideration as fixation goes from 0 to 1 should be larger than the increase as fixation goes from 1 to 2+. In other words, there are diminishing returns in the gain from each additional look. This is because the additional chance of considering the brand after each fixation is the memory-based probability (β_j) weighted by a term smaller than 1 (because $0 \leq \alpha_j \leq 1$ and $0 \leq \beta_j \leq 1$) for the first eye fixation and by an even smaller term for the second fixation (derivation available from the authors). This too is consistent with our data (i.e., .07 vs. .06 for juices and .06 vs. .04 for detergents, see Figure 4). Thus, the model is able to capture important qualitative aspects of our empirical data.

One important aspect of the decision-path model is that it also allows for a decomposition of consideration probabilities. It is natural to think of β_j as a measure of memory-based consideration and the increase in consideration due to in-store visual attention as a measure of visual lift. Specifically:

$$VL_j \quad = \quad c_j - \beta_j \quad = \quad \beta_j\, \alpha_j\, (1 - \beta_j) + \beta_j\, \alpha_j^2\, (1 - \beta_j)^2 \qquad (2)$$

Visual lift is jointly determined by the visual salience of the brand (α_j) and by the memory-based consideration of the brand (β_j). This is an important aspect of the model because it shows that simply raising visual salience is not enough. For example, raising visual salience does not create any visual lift in the two extreme cases of zero or 100% memory-based consideration probabilities (e.g., for brands liked by nobody or by everybody). Figure 6 plots total brand consideration (c_j) as a function of memory-based response (β_j) for minimum ($\alpha_j = 0$), moderate ($\alpha_j = .33$), typical ($\alpha_j = .67$), and maximum ($\alpha_j = 1$) levels of visual salience. The vertical arrows in Figure 6 show maximum visual lift for each level of memory-based response, β_j. As Figure 6 shows, visual salience (α_j) increases visual lift for all levels of memory-based response (except of course when $\beta_j = 0$ or $\beta_j = 1$). In contrast, visual lift first increases and then decreases as memory-based response (β_j) increases.

--- Insert Figures 6 and 7 here ---

Visual lift, VL_j, provides a natural performance measure because the unit of measurement is incremental probability of consideration, and it reflects the assumption that the effects of visual salience on choice are mediated by inclusion in the consideration set. However, it does not answer the question of which brands should receive incremental P-O-P dollars, a decision directly relevant for manufacturers and retailers. To shed light on this complex decision, we compute another index, visual responsiveness,

$$VR_j \quad = \quad \mathrm{d}c_j \,/\, \mathrm{d}\alpha_j \,, \tag{3}$$

which is the same as $\mathrm{d}VL_j \,/\, \mathrm{d}\alpha_j$ because $VL_j = c_j - \beta_j$ and β_j is not a function of α_j.

Visual responsiveness, VR_j, is also a function of visual salience (α_j) and memory-based response (β_j) and is plotted in Figure 7. From this figure we see that brands with moderate levels of memory-based response provide the best return on P-O-P investments. More specifically, as α_j increases from 0 to 1, the value of β_j with maximum responsiveness (β_j*) shifts from .50 to .39 (derivation available from the authors). We show how visual responsiveness can help marketers decide which brand should be made more visually salient, in theory and for the brands studied here, in the next section.

Model Estimation

As can be seen in Figure 6, for any given value of α_j, c_j is a monotonically increasing function of β_j. This function can be inverted to compute β_j from α_j and c_j :

$$\beta \quad = \quad \frac{1}{6\alpha^2}\left[2\alpha(1+2\alpha)+\frac{2\cdot 2^{1/3}\alpha^2\left(-2+\alpha+\alpha^2\right)}{k^{1/3}}+2^{2/3}k^{1/3}\right], \tag{4}$$

where k =

$$-7\alpha^3-15\alpha^4-3\alpha^5-2\alpha^6+27\alpha^4c+\sqrt{4\left(2\alpha^2-\alpha^3-\alpha^4\right)^3+\left(-7\alpha^3-15\alpha^4-3\alpha^5-2\alpha^6+27\alpha^4c\right)^2}$$

.

In principle, this computation could be made even when the empirical values of α_j and c_j come from different sources (e.g., a standard eye-tracking report and a survey measure of memory-based consideration). However, this computation is exact and provides no statistical measures of reliability or validity. Fortunately, the eye-tracking studies described earlier provide richer data. For each brand, our two-parameter model can be estimated via maximum likelihood from the frequencies with which each of the six possible outcomes occur using the equations in (A1) and (A2)[3].

--- Insert Figure 8 here ---

In Figure 8, observed consideration (dashes) and consideration predicted by our model (open circles) are plotted as a function of estimated memory-based response for the juice data (similar results were obtained for detergents, but are omitted here to simplify the discussion). As in Figure 6, the vertical bars represent maximum visual lift. Finally, the dotted line represents the maximal predicted consideration under certain visual attention (α_j = 1) and the solid line the (memory-based) minimal level of predicted consideration under no visual attention (α_j = 0). The distance from the diagonal to the observed consideration marker (open circle) represents the estimated visual lift, VL_j, based on the model. As Figure 8 shows, the fit of our model to the data is quite good. The predicted and observed consideration values are

[3] We used the Solver add-in of Microsoft Excel to maximize the following equation LL = $\Sigma_j\ \Sigma_i$ $\ln(I_{i0n_j}\ p_{0n_j} + I_{i1n_j}\ p_{1n_j} + I_{i2n_j}\ p_{2n_j} + I_{i0y_j}\ p_{0y_j} + I_{i1y_j}\ p_{1y_j} + I_{i2y_j}\ p_{2y_j})$ across brands j and consumers i, where I is an indicator function that is 1 for the observed fixation/consideration outcome and 0 otherwise. Using multiple starting values for a subset of the analyses checked the operational robustness of the algorithm. These replications almost always converged to virtually identical solutions, indicating that local maxima were generally not a problem. Also, the correlations between the exactly computed and maximum likelihood estimated values of β_j are very high (.999 for juices and 1.000 for detergents).

very close (paired t-value = .36, df = 15, p = .57, η^2 = .02 for juices and paired t-value = .71, df = 9, p = .42, η^2 = .04 for detergents).

The estimation results show that, on average, observed consideration probabilities are a combination of memory-based response and visual lift in roughly equal proportions for both juices and detergents (c = .157, β = .076, and VL = .081 for juices and c = .228, β = .114, and VL = .115 for detergents). Of course, these average values hide important differences between brands. For example, visual responsiveness varies between .01 and .37 for juices and between .02 and .49 for detergents. Estimated values of visual salience, memory-based response, visual lift, and visual responsiveness are also given in Figure 2, for juices, and in Figure 3, for detergents. We illustrate the managerial usefulness of these differences in visual lift and visual responsiveness after testing the robustness of the simple model to the assumption of the independence of α_j and β_j.

Robustness with Respect to Model Specification

To test the robustness of our model, we also estimated a more general version that (1) allowed β_j (i.e., memory-based response) to change as a result of fixating on the brand (i.e., in-store) or not (i.e., out-of-store), (2) allowed all parameters to vary by segment (i.e., non-users, occasional users, and regular users), and (3) incorporated heterogeneity by using a hierarchical Bayesian model. In particular, the logit of the individual-level fixation and consideration parameters for a specific brand, by a given respondent, in a particular usage segment, was modeled as having a main-effect term for persons, brand, and segment, and an interaction term of brand by usage segment. As is standard in Bayesian models, these parameters were then given Gaussian prior distributions and corresponding conjugate hyperpriors to allow for appropriate uncertainty estimation. The model was fit in the freely available software WinBUGS (URL=http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml); the code and computation details are available upon request from the authors.

--- Insert Figure 9 here ---

For the simple models discussed thus far, the Bayesian parameter estimates replicated the maximum likelihood estimates almost exactly. Also, for most versions of the model, post-fixation consideration probabilities were non-zero (and similar in size to pre-fixation probabilities), rejecting the hypothesis that all consideration is out-of-store and visual lift is zero. However, results for some versions of model revealed interesting changes in parameter estimates and suggested important limitations to the current data. When fixation probabilities were allowed to differ for not-yet-considered and already-considered brands in the decision path model, the estimated probabilities were larger for already-considered brands. This resulted in larger estimates of base consideration and smaller estimates for post-fixation consideration. These changes reduced visual lift considerably; in some cases, to zero. However, this seems to be the result of a key indeterminacy for observational (i.e., non-experimental) data such as these. Models with much larger levels of post-fixation consideration and visual lift fit the data nearly as well. In fact, distinct bimodality was often observed for these parameters in their posterior distributions. Figure 9 shows these distributions for the juices data. The bimodality is particularly evident for occasional users. An important problem for future research is to find ways to resolve this type of indeterminacy.

IMPLICATIONS FOR P-O-P MARKETING

Estimating the Visual Salience of Different Areas of Supermarket Displays

Our results show consistent patterns of visual attention across the different areas of the shelf. As can be seen in Figures 2 and 3, brands located near the center of the shelf are seen by almost all consumers (e.g. α = .92 for Minute Maid Concentrate and α = .89 for Purex). The likelihood of noting the brand then drops very quickly as one moves towards the end of the display (e.g., α = .52 for Pathmark Premium and α = .44 for Surf, two brands located at the bottom left end of their respective shelves). In order to explore the factors affecting visual salience, we regressed it onto a binary variable representing bottom shelf (vs. top or middle shelf), a binary variable representing brands located to the left, and another binary variable representing brands located to the right (for juices only; the right location being confounded with Tide for detergents), and on the number of facings. The coefficients for bottom shelf were: B = -.11, t = -2.50 for juices and B = -.17, t = -2.63 for detergents; for left location: B = -.18 , t = -3.43 for juices and B = -.20, t = -3.61 for detergents; for right location: B = -.08, t = -1.94 for juices; and for number of facings: B = -.00, t = -.27 for juices and B = .02, t = .98 for detergents. Thus, there were clear effects of location, but little effect of shelf facings.

Of course, our data do not allow to perfectly isolate the effects of these variables and to disentangle them from brand-specific effects. For example, the current displays do not allow testing the visual salience of brands on the top shelf because the top juice shelf contained brands with many facings and the top detergent shelf contained brands located also on the middle shelf. This is clearly an area for future research, involving either the analysis of many varied displays, or an experimental design in which brand, shelf location, and number of facings are orthogonally manipulated. On the other hand, our results suggest that the patterns of visual salience identified here may be fairly robust given that they hold on two categories with considerable differences in visual display and purchase behavior.

Estimating the Effects of Visual Attention across Brands

Our results reveal large differences across brands for visual lift and responsiveness (see Figures 2 and 3). Brands with many shelf facings or a central location, like Minute Maid Concentrate and Cheer, performed well insofar as visual lift is high compared to memory-based response (β = .18 and VL = .24 for Minute Maid Concentrate and β = .14 and VL = .18 for Cheer) and their consideration is near the maximum value possible as estimated by our model (see Figure 8). In contrast, brands like Sunny Delight and Wisk have high levels of memory-based response (comparable to Minute Maid Concentrate and Cheer), but much lower visual lift (β = .17 and VL = .15 for Sunny Delight and β = .15 and VL = .11 for Wisk), and hence much lower overall level of consideration. A similar problem is evident for Surf and Pathmark Premium, which too have substantial room for improvement. We note that all four of these identified "poor performers" are located on the left end of the shelf display, suggesting that this is a low visual lift region of the display. Further analysis is necessary to understand why these brands do not gain as much from each in-store attention as other brands. In any case, one direct use of our measures is to aid managers in identifying potential problem areas in their P-O-P activities.

It is also important to note that the values of memory-based-response and visual lift, per se, do not tell the whole story. In order to evaluate the relative P-O-P performance of different brands, one needs to consider visual lift in relation to its maximum value. For example, as can be seen in Figures 2 and 8, Sunny Delight has slightly higher visual lift than Dole (.15 vs. .13), but is much further from it's maximum level of visual lift, the difference between memory-based consideration and maximal consideration under perfect visual salience (which is .27 for Sunny Delight vs. .15 for Dole). This analysis shows that Sunny Delight has much more room for improvement than Dole, and thus suggest that it should be selected for improved P-O-P activity (e.g., it should receive a shelf talker); albeit profit considerations are required.

Optimal Allocations of In-store Visual Salience

In the two categories studied, the brands with highest visual responsiveness are those with highest levels of memory-based response (VR = .37 for Minute Maid from Concentrate and VR = .49 for Tide). This raises the more general question of which brands would benefit the most from additional visual salience, and hence of which brand should receive incremental P-O-P dollars. In practice, manufacturers typically want to improve their weakest brands (e.g., to promote trial of new products). Retailers, in contrast, typically give the most effort to strong brands, with the rationale that they are the most likely to trigger category sales (Drèze et al. 1994). The general optimization problem faced by retailers is very complex because the control variables are many (e.g., shelf locations, numbers of facings, and shelf talkers for each brand in a product category), brands differ (e.g., in brand equity, advertising support, price and profit margin), and the causal impact of P-O-P activities is uncertain and may vary across brands. In this section, we use the decision-path model to abstract away from these complexities and obtain results that shed light on how incremental changes in P-O-P marketing can be optimized.

To simplify the analysis, we first assume that there is a reasonably direct relationship between consideration probabilities and sales and, therefore, profit. That is, we assume the goal is to maximize total consideration across brands and shoppers (and that consideration is statistically independent across brands and shoppers). Second, we assume that visual salience (α_j) is under the control of the manager, but that memory-based response (β_j) is exogenously determined for a finite set of brands that are being managed (i.e., as a retailer's assortment or as a manufacturer's product line). Finally, we assume that cost is linearly related to visual salience.

Given these assumptions, standard economic reasoning dictates that each incremental dollar spent on improving in-store visual salience should be spent where it will do the most good. That is, it should be spent on the brand whose consideration will increase most as a result. Moving beyond small increments to allocating a finite budget across a set of discrete alternatives requires solving some type of "knapsack" problem. Problems of this sort are extremely complex mathematically and are typically solved numerically for specific variations of the problem. One method of solution is to use a "greedy algorithm" that makes a series of small incremental improvements until a local maximum is achieved (Kohli and Krishnamurti 1995).

Visional responsiveness (VR_j) measures the impact of incremental changes in visual salience (α_j) on brand consideration. As shown in Figure 7, for any given level of memory-based response, visual responsiveness increases with the level of visual salience of the brand. Thus, there are marginally increasing returns to visual salience (Implication 1). It is also evident in Figure 7 that visual responsiveness is maximal for brands with moderate levels of memory-based equity (Implication 2). It does not pay to increase the visual salience of brands with low memory-based probability of consideration because incremental fixations are likely to lead to negative consideration decisions. Brands with very high memory-based response do not gain much from higher visual salience because they are likely to have already been considered. This result already shows that the common practice of allocating shelf space according to market share (a proxy for memory-based equity) may not be optimal for very strong brands, which are likely to be in the diminishing portion of the VR_j curve in Figure 7.

To illustrate these two implications, consider four hypothetical brands depicted in Figure 7 as *a*, *b*, *c*, and *d*. The most responsive brand is *a*, so it should receive incremental P-O-P effort. Because increasing the visual salience of *a* will make it even more responsive, it would receive the next increment and so on until it achieved maximum visual salience (Implication 1). Using the same reasoning, subsequent allocations would be made to brand *b* until it achieved its maximum visual salience. Brands *c* and *d* have the same visual responsiveness. However, if the same incremental allocation is made to both brands (e.g., raising visual salience of each by .33, making *c* equivalent to *a* and *d* equivalent to *b*), then the resulting responsiveness of *c* will exceed that of *d*. Thereafter, all subsequent allocations would go to *c* until it reached its maximum. This same logic applies to solutions obtained using a greedy algorithm.

In terms of visual salience and memory-based equity, brand *a* is the strongest in the set. Thus, this example suggests that a "stick-with-the-winner" strategy for making P-O-P allocations should be optimal in many situations. This strategy gives all incremental allocations to the "strongest" brand until it reaches its maximum and then allocates to the next-strongest brand and so on until further allocations are no longer profitable. We contrast this with a "help-the-poor" strategy in which all incremental allocations are given to the "weakest" brand until it reaches its maximum and then allocate to the next strongest brand and so on until further allocations are no longer profitable.

In general, the optimality of stick-with-the-winner strategy will depend on how brand strength is defined and the relative strengths of the brands in the set over which allocations are made. One natural, but conservative, definition is that one brand is stronger than another, if it has higher values of both visual salience and memory-based equity (i.e., a weak ordering on all brands in the (α, β) space). Thus, in our example, *a* is stronger than *c* and *d*, and *b* is stronger than *d*, but the remaining pairs cannot be ranked. Given this definition of strength it is easy to show that if a finite set of brands is strictly ordered by strength and the maximum value of β_j is less than .39, then the stick-with-the-winner strategy will be optimal. No similarly general results emerge if the ordering is not strict or if β_j is greater than .39 for some brands.

To obtain more general results, we explored the concept of brand strength in a series of numerical analyses. In these analyses, a discrete improvement in visual salience was applied to pairs of brands that differed in strength, and the resulting gains in visual lift were compared. In particular, it was assumed that a specific P-O-P action resulted in an independent probability, Δ, that the brand would be noted at each point in the decision path where the base probability, α_j, was applied. Thus, the new probability of fixation, α_j', was equal to $\alpha_j + \Delta - \alpha_j \Delta$. This is a natural way to represent singular actions such as adding a shelf-talker or end-aisle display for a brand. It also imposes a plausible form of diminishing returns that works against the stick-with-the-winner strategy, making this a conservative test. The gain in visual lift from such a discrete action is:

$$\begin{aligned} GAIN_j &= VE_j' - VE_j \\ &= \beta_j (\Delta - \alpha_j \Delta) (1 - \beta_j) (1 + (\Delta - \alpha_j \Delta + 2\,\alpha_j) (1 - \beta_j)). \end{aligned} \tag{5}$$

In our numerical analyses, brand 1 was assumed to be stronger than brand 2 (i.e., $\alpha_1 \geq \alpha_2$ and $\beta_1 \geq \beta_2$). We define gain advantage of brand 1 over brand 2, A_{12}, as

$$A_{12} = GAIN_1 - GAIN_2. \tag{6}$$

Thus, the sign of A_{12} is an indicator of the superiority of the stick-with-the-winner strategy and the size of A_{12} represents the cost of choosing the wrong strategy. A_{12} is a function of 5 parameters (α_1, α_2, β_1, β_2, and Δ), so our approach was to randomly sample parameters and identify regions of the space where A_{12} is predominantly positive or negative.

In our analysis, 2,000 observations were generated by (1) independently drawing Δ, α_1, and β_1 from the uniform distribution on [0,1], (2) drawing α_2 and β_2 conditionally from uniform distribution on $[0,\alpha_1)$ and $[0,\beta_1)$, respectively, and (3) computing A_{12}; of course with the restriction that all probabilities remain between [0,1]. A_{12} was negative for 61% of the observations and had an average value of -.02. Thus, across all possible situations the help-the-poor strategy is slightly favored. Also, the optimal strategy shifts from stick-with-the-winner to help-the-poor as Δ, α_1, and β_1 increase (i.e., the help-the-poor strategy is preferred for P-O-P activities with a large impact on visual salience or when the stronger brand is really strong). A regression of A_{12} onto Δ, α_1, β_1, α_2, and β_2 accounted for 44% of the variance in A_{12} and yielded standardized coefficients of -.19, -.47, -.21, .26, and -.35 for Δ, α_1, β_1, α_2, and β_2, respectively. All coefficients were statistically significant. However, an examination of marginal distributions revealed much stronger and more meaningful results: A_{12} was always negative whenever β_2 (and therefore β_1 also) was greater than .43, indicating that the help-the-poor strategy dominates as long as memory-based equity is at least moderate for both brands. If we operationally define "impulse brands" to be those with memory-based equity less than .43 and "destination brands" as those with memory-based equity greater than .43, then we can generalize these results from pairs to sets of brands as follows: (1) when all brands are impulse brands, use the stick-with-the-winner strategy, and (2) when all brands are destination brands, use the help-the-poor strategy.

CONCLUSIONS AND FUTURE RESEARCH OPPORTUNITIES

In an era when consumers seem overwhelmed by the number of available products, marketers are investing large amounts of money and effort to ensure that their brands are seen at the point of purchase. Yet, it has been difficult to measure the return on these investments because few data and methods are available to estimate visual lift, the incremental consideration due to in-store visual attention over pre-store memory-based consideration. Ideally, marketers would decompose sales into out-of-store, memory-based response and in-store visual lift, similar to the commonly used decomposition of sales into baseline and promotional volumes.

In this paper, we have shown that commercial eye-tracking data, analyzed using a simple decision-path model of visual attention and brand consideration, can provide this type of decomposition. Moreover, our empirical applications and normative analysis show that allocating P-O-P marketing activity according to market shares can be wrong. If all brands have a low memory-based probability of consideration (e.g., for "impulse" brands), retailers should "stick with the winner" (i.e., focus on the strongest brand until it reaches its maximum and then move to next-strongest brand and so on until further allocations are no longer profitable). If all brands have a high memory-based probability of consideration (e.g., for "destination" brands), retailers should use the opposite "help-the-poor" strategy. Finally, our analyses provide new insights into how consumers make consideration and attention decisions at the point of purchase.

This research opens several areas for future investigation. Showing that in-store visual attention increases brand consideration naturally raises the issue of what influences in-store attention. Future research could examine the effects of factors such as shelf position, the number of facings, and price on fixation and consideration probabilities by testing a series of planograms in which these factors are independently manipulated (for more on the effects of product design and spatial location, see the chapters by Krishna and Raghubir in this volume). This would provide sufficient degrees of freedom to examine temporal dependencies in fixation and consideration probabilities and to incorporate brand and customer heterogeneity. More importantly, this would allow us to better test the direction of the causality between attention and consideration.

Additionally, it would be valuable to know whether visual attention to shelf displays is mainly controlled by automatic and non-conscious processes requiring little or no cognitive capacity, or if consumers are able to locate pre-selected brands without being distracted by visual factors that are simply too salient to ignore. Another important research issue is determining the extent to which researchers can measure visual attention without needing to collect eye-tracking data. For example the common Starch scores of exposure actually measure consumer's recollection of having previously seen the ad. However, it remains to be seen whether asking consumers to recall the brands that they have seen could be used as an indicator of their visual attention to the brand.

Appendix A: Details of Model Specification

To highlight the tree-like structure of our model for fixation and consideration, we present in equations (A.1.1) - (A.1.9) below, a series of step-by-step probabilities that are not algebraically simplified. Each of these corresponds to a different latent path and their link to observable outcomes are described below in equations A.2 - A.5

$$p1j = (1-\beta_j)\,(1-\alpha_j), \tag{A.1.1}$$

$$p_{2j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)\,(1-\alpha_j), \tag{A.1.2}$$

$$p_{3j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)\,\alpha_j\,(1-\beta_j), \tag{A.1.3}$$

$$p_{4j} = (1-\beta_j)\,\alpha_j\,(1-\beta_j)\,\alpha_j\,\beta_j, \tag{A.1.4}$$

$$p_{5j} = (1-\beta_j)\,\alpha_j\,\beta_j\,(1-\alpha_j), \tag{A.1.5}$$

$$p_{6j} = (1-\beta_j)\,\alpha_j\,\beta_j\,\alpha_j, \tag{A.1.6}$$

$$p_{7j} = \beta_j\,(1-\alpha_j), \tag{A.1.7}$$

$$p_{8j} = \beta_j\,\alpha_j\,(1-\alpha_j), \text{ and} \tag{A.1.8}$$

$$p_{9j} = \beta_j\,\alpha_j\,\alpha_j. \tag{A.1.9}$$

For each person and brand, an observation is one of the six possible events defined by three levels of fixation (0, 1, and 2 or more) and two consideration outcomes (y = yes or n = no). The probabilities for the events observed in our data are easily computed from the path probabilities as follows.

$$p_{0nj} = p_{1j}, \tag{A.2.1}$$

$$p_{1nj} = p_{2j}, \tag{A.2.2}$$

$$p_{2nj} = p_{3j}, \tag{A.2.3}$$

$$p_{0yj} = p_{7j}, \tag{A.2.4}$$

$$p_{1yj} = p_{5j} + p_{8j}, \text{ and} \tag{A.2.5}$$

$$p_{2yj} = p_{4j} + p_{6j} + p_{9j}. \tag{A.2.6}$$

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TABLE 1

DESCRIPTIVE STATISTICS FOR THE JUICES AND DETERGENT STUDIES

(MEANS AND STANDARD DEVIATIONS)*

	Juices	Detergents
Visual display characteristics		
Visual area of brand on screen† (sq inches)	118.80 (59.42)	189.00 (94.39)
Price† ($)	2.80 (.51)	3.88* (.66)
Consumer purchase behavior		
Number of brands used regularly or occasionally‡	12.29 (3.70)	6.86** (2.81)
Brand loyalty‡a	.52 (.50)	.64* (.48)
Degree of impulse purchasing‡b	.37 (.48)	.20** (.40)
Visual attention and consideration		
Time spent on picture‡ (seconds)	25.06 (21.6)	17.99** (9.35)
Number of brands (pack or price) fixated at least once‡	10.93 (3.46)	7.09** (2.23)
Number of packs fixated at least once‡	10.54 (3.46)	6.90** (2.17)
Number of prices fixated at least once‡	4.04 (2.68)	2.52** (2.00)
Number of brands considered‡	2.57 (1.81)	2.29 (1.30)

NOTES:
† These are average values across brands (n = 16 for juices, n = 10 for detergents).
‡ These are average values across consumers (n = 159 for juices, n = 150 for detergents).
[a] Percentage of consumers who state that they "always buy the same brand regardless of price" or "regularly buy one brand unless there is a sale," rather than either "switch between brands" or "buy the cheapest brand.
[b] Percentage of consumers who state that they "usually decide whether or not to buy from the category when they are in the store," rather than "before entering the store".
** p < .01, * p < .05.

FIGURE 1

A FRAMEWORK OF THE EFFECTS OF VISUAL ATTENTION AND MEMORY AT THE POINT OF PURCHASE

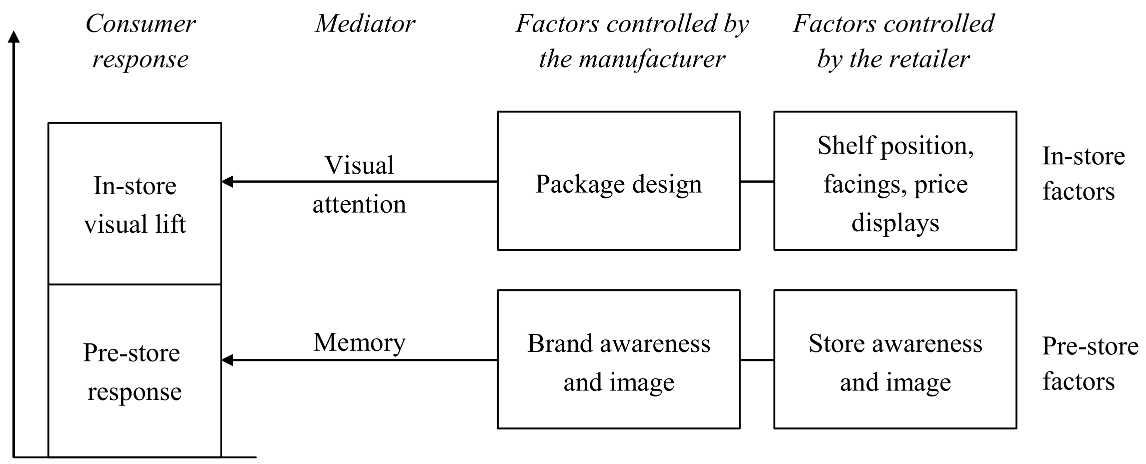


FIGURE 2

SHELF LAYOUT AND BRAND RESULTS FOR JUICES

Legend α = Visual salience. C = Consideration frequency. β = Memory-based response. *VL* = Visual lift (C–β). *VR* = Visual responsiveness ($dC/d\alpha$).

FIGURE 3

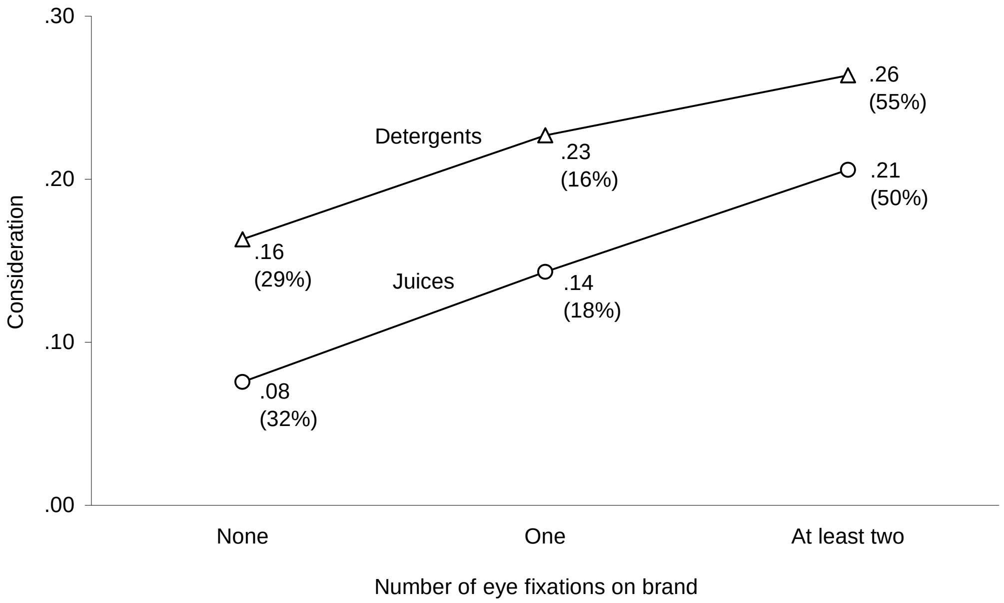
SHELF LAYOUT AND BRAND RESULTS FOR DETERGENTS

Legend α = Visual salience. C = Consideration frequency. β = Memory-based response.
VL = Visual lift (C–β). *VR* = Visual responsiveness ($dC/d\alpha$).

FIGURE 4

CONSIDERATION CONDITIONAL ON NUMBER OF FIXATIONS

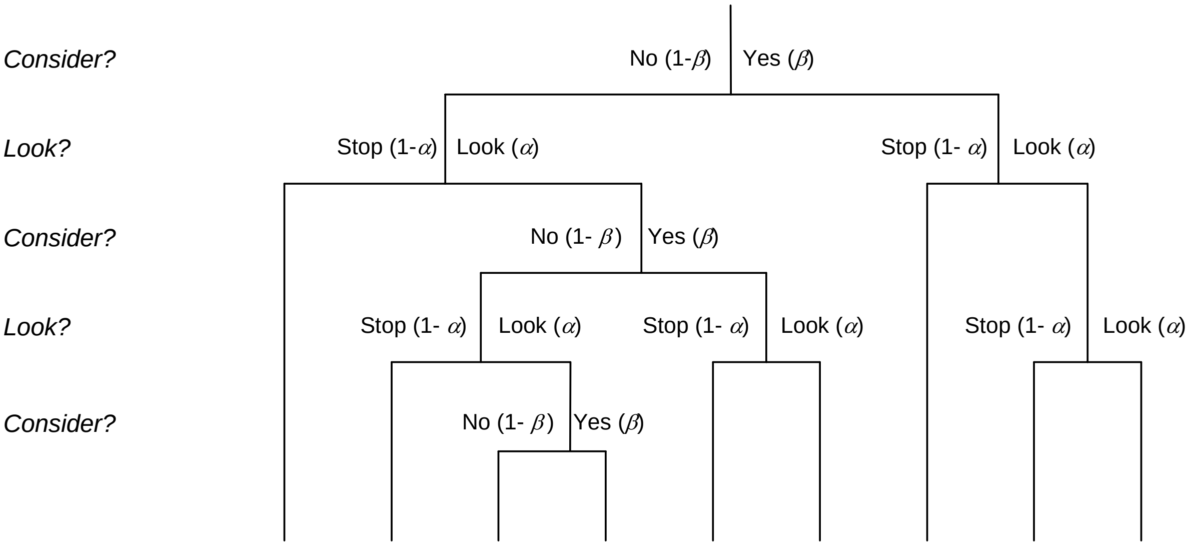
AND RELATIVE FREQUENCY OF NUMBER OF FIXATIONS (IN PARENTHESES)



NOTE: These are average values across brands (defined as pack, price, and, if present, shelf talker).

FIGURE 5

A DECISION-PATH MODEL OF POINT-OF-PURCHASE DECISION MAKING



Decision path	1	2	3	4	5	6	7	8	9
Number of looks	0	1	2+	2+	1	2+	0	1	2+
Consideration	no	no	no	yes	yes	yes	yes	yes	yes
	No consideration			In-store visual lift			Pre-store consideration		

NOTE: α is the probability of an eye fixation on the brand (its visual salience) and β is the probability of considering the brand. In this simple version of the model, β is fixed for each brand and is therefore also the memory-based probability of considering the brand.

FIGURE 6

CONSIDERATION AND VISUAL LIFT AS FUNCTIONS OF VISUAL SALIENCE (α) AND MEMORY-BASED RESPONSE (β)

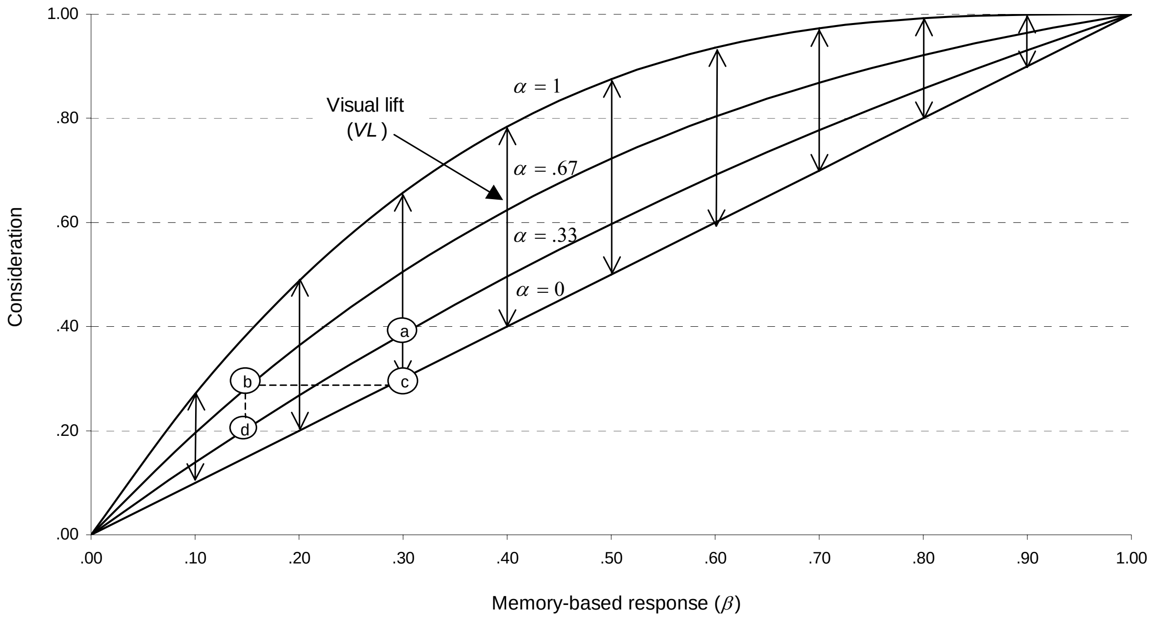


FIGURE 7

VISUAL RESPONSIVENESS AS A FUNCTION OF VISUAL SALIENCE (α) AND MEMORY-BASED RESPONSE (β)

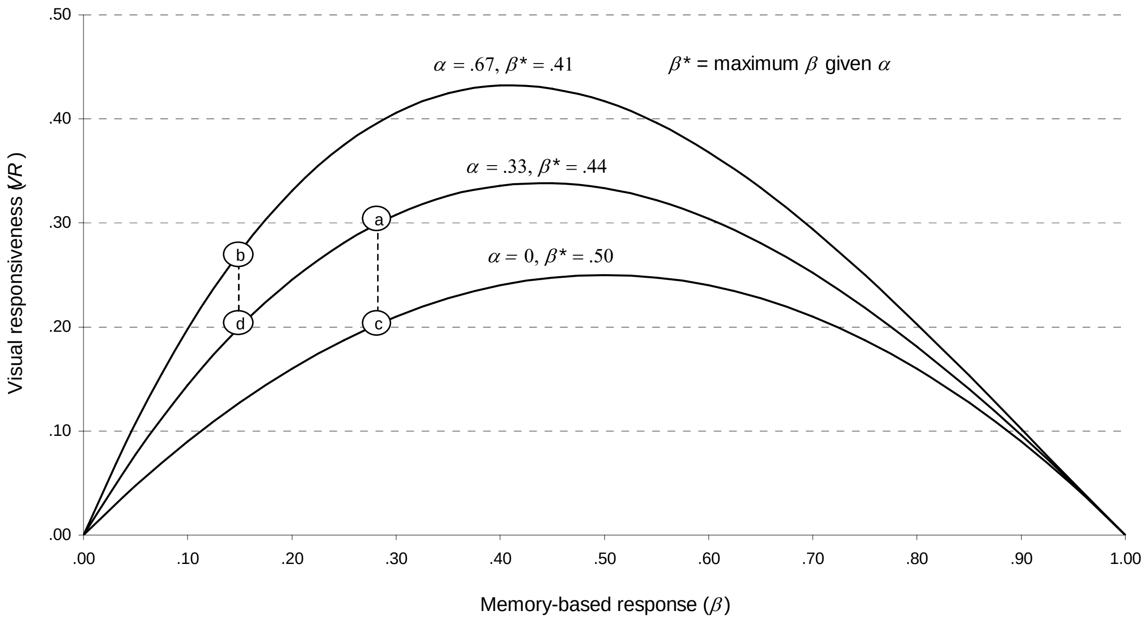


FIGURE 8

OBSERVED, PREDICTED CONSIDERATION, VISUAL LIFT, AND MEMORY-BASED RESPONSE ESTIMATES FOR JUICES

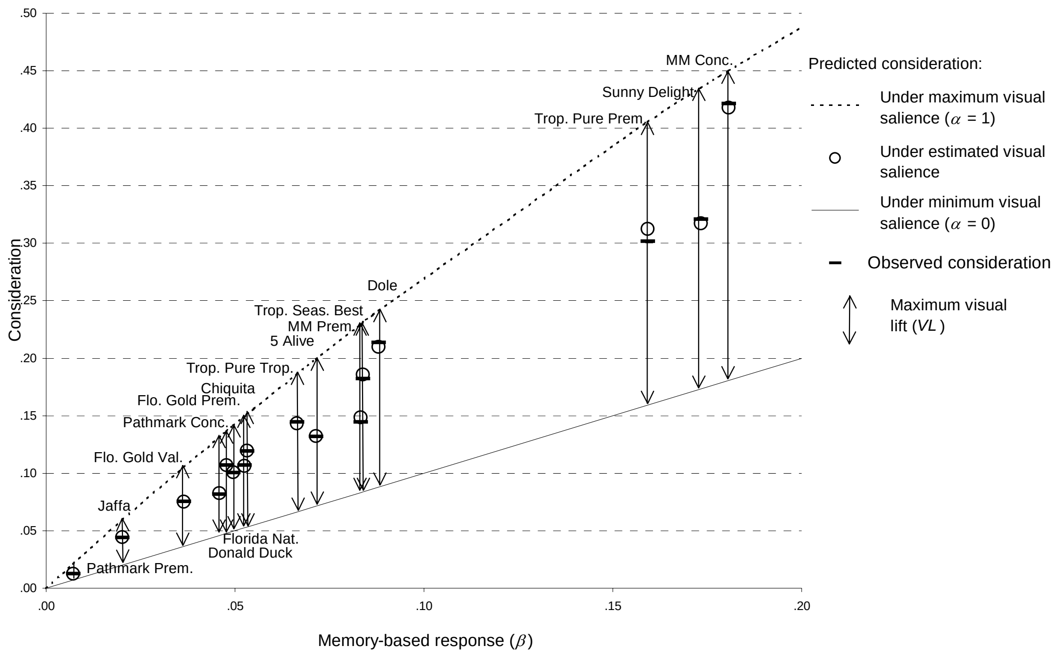
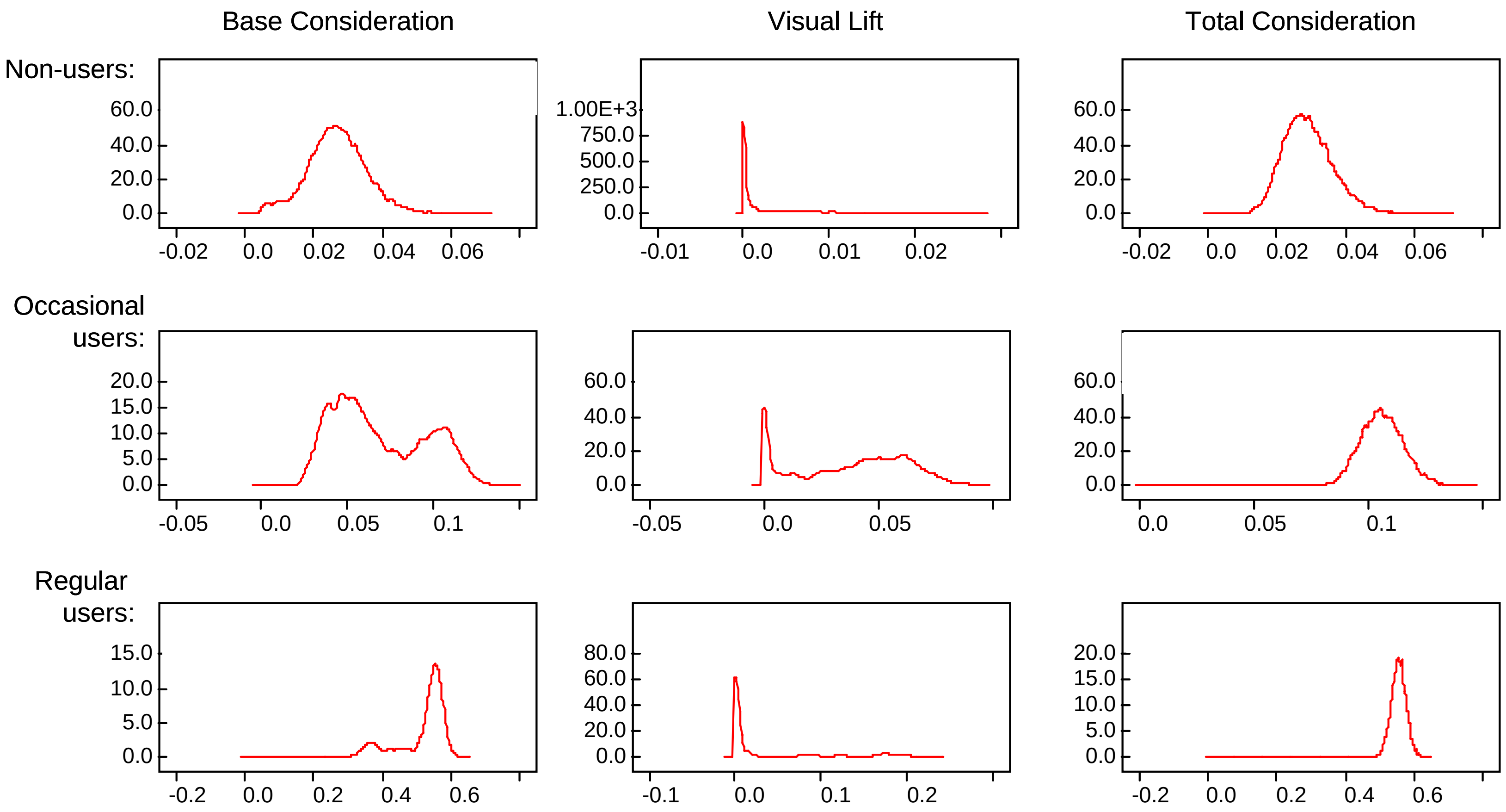


FIGURE 9

MODEL ESTIMATION RESULTS USING HIERARCHICAL BAYES METHOD: POSTERIOR DISTRIBUTIONS FOR JUICES



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