MARTIN MEIßNER, ANDRES MUSALEM, and JOEL HUBER*

Choice-based conjoint is a popular technique for characterizing consumers' choices. Three eye-tracking studies explore decision processes in conjoint choices that take less time and become more accurate with practice. These studies reveal two simplification processes that are associated with greater speed and reliability. Alternative focus gradually shifts attention toward options that represent promising choices, whereas attribute focus directs attention to important attributes that are most likely to alter or confirm a decision. Alternative and attribute focus increase in intensity with practice. In terms of biases, the authors detect a small but consistent focus on positive aspects of the item chosen and negative aspects of the items not chosen. They also show that incidental exposures arising from the first-examined alternative or from alternatives in a central horizontal location increase attention but have a much more modest and often insignificant impact on conjoint choices. Overall, conjoint choice is found to be a process that is (1) largely formed by goal-driven values that respondents bring to the task and (2) relatively free of distorting effects from task layout or random exposures.

Keywords: eye tracking, conjoint, choice models, incidental exposure, goal-driven processes

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Eye Tracking Reveals Processes That Enable Conjoint Choices to Become Increasingly Efficient with Practice

Observation of eye movements has provided significant insights into the processes underlying consumer product choice. In the current research, eye tracking enables a clearer understanding of the processes that respondents use when completing a conjoint exercise that involves repeatedly choosing among alternatives that are assigned different features across tasks. The results of three empirical studies show that the process is relatively efficient and has a particularly simple structure in which attention is directed toward attractive alternatives and important attributes. Alternative focus consistently increases as the decision approaches. Furthermore, with experience across tasks, respondents make faster decisions and attend to more important attributes and more attractive alternatives. These processes are consistent with a goal-driven causality mechanism whereby attention depends on stable values that each respondent brings to the task.

Eye tracking enables us to assess whether task layout or random exposures distort attention and choice. We find that respondents' attention to features within an alternative is affected by whether they choose that alternative, with relatively more attention paid to positive than to negative features of chosen objects. However, we find little evidence

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that stimulus-driven attention influences choice in repeated conjoint tasks. The empirical results show that both the alternative examined first and the centrally positioned alternative receive more attention, but this additional attention does not reliably increase one's probability of choosing that alternative. The major finding of our research is that the main drivers of both attention and choice are the stable utility values that people bring to the task.

In the first two sections of the article, we review research on general choice processes that characterize when attention arises from respondents' goal-driven values and when it arises from the stimulus-driven properties of the task. In the following section, we explore the ways conjoint choice processes can be expected to differ from one-time, unstructured decisions, and we pose a series of research questions the studies are designed to answer. We then present results from three conjoint studies that arise from different product categories, choice designs, and choice tasks. We report relatively simple analyses that clarify ways in which conjoint choices can be distorted by common contextual biases and show that the focus on attractive alternatives and important attributes allows for more effective conjoint choices. We then complement these initial analyses with a Poisson model of the count of fixations on each product feature. This model simultaneously accounts for multiple factors that can alter attention. Those analyses more clearly reveal the processes by which value-based attention develops within and across choice tasks.

Although this article reveals a process of conjoint choices that is quick, efficient, and less susceptible to common contextual biases, there are several related issues that go beyond its scope. First, in terms of process, we characterize attentional focus within and across the conjoint choices. However, unlike Shi, Wedel, and Pieters (2012), we do not consider transitions between individual fixations or latent cognitive states that reflect processing shifts. We also do not develop a search model based on attentional information (Reutskaja et al. 2011) or a joint model of information processing and choice, as other authors have done (Gabaix et al. 2006; Yang, Toubia, and De Jong 2015). Finally, although process data can increase the likelihood of correctly predicting choice (Stüttgen, Boatwright, and Monroe 2012; Willemsen, Böckenholt and Johnson 2011), our focus is not on prediction but on understanding the processes of conjoint choices and characterizing how conjoint choice exercises are successful in identifying stable values that underlie trade-offs.

GOAL- AND STIMULUS-DRIVEN ATTENTION

Two mechanisms jointly explain attentional processes in choice tasks: goal- and stimulus-driven attention (Orquin and Mueller Loose 2013). Goal-driven attention occurs when attended alternatives and attributes correspond with respondents' decision goals and enduring values. Stimulus-driven attention occurs where attention is altered by incidental characteristics of a stimulus related to its salience, location, or forced exposure. We propose that distortion of choices is possible under both mechanisms: goal-driven attention can lead to heuristics and shortcuts that result from trying to quickly identify a satisfying decision alternative, whereas stimulus-driven attention can directly distort choices if incidental attention to an alternative increases the probability that it is chosen.

Evidence for Goal-Driven Attention and Choice

The normative goal of choice is to select a satisfying alternative while limiting time and effort (Yang, Toubia, and De Jong 2015). Next, we review research that documents that increasing attention to promising alternatives and important attributes is associated with generating a choice with high utility. Then, we show how the goal of increasing certainty and decreasing effort may lead to motivated attention and a shift in values that increases the likelihood of choosing the current alternative.

Alternative focus. Studies have consistently shown that the chosen alternative receives substantially more attention than nonchosen alternatives (Pieters and Warlop 1999; Shimojo et al. 2003). Recent research has replicated this result using eye tracking for choice tasks presented in an attribute-by-product matrix (Shi, Wedel, and Pieters 2012).

Willemsen, Böckenholt, and Johnson (2011) provide an example of the close correspondence between attention and search by demonstrating how the current evaluation of an alternative can influence subsequent search for information. When an alternative becomes the preliminary leader, respondents focus more attention on it. Information search and comparison processes are then more favorably disposed toward the features of that leading alternative, producing more attention toward the chosen alternative that becomes stronger as the decision approaches.

We show that high-valued alternatives in conjoint choice tasks receive increased attention. We add to this research on alternative focus by assessing the extent to which the focus on attractive alternatives increases with task progression and with experience across choice tasks.

Attribute focus. Researchers have also investigated whether information is gathered differently for different attributes. Investigating search patterns using Mouselab's process-tracing tool, Johnson et al. (1997) show that respondents use brands to screen a choice set early on (indicated by more attribute-wise processing, greater variability in search, and the fact that brands were more often looked at in the first half of the choice process), whereas the characteristics of brands become more important later in the search process. Harte, Koele, and Van Engelenburg (1996) compare attribute importance measures derived from an estimation of multiattribute utilities with attribute weights from information-display boards that capture the amount of information searched. They observe an average correlation of approximately .9 between estimated multiattribute utilities and attribute attention weights, demonstrating that important attributes receive more attention.

In line with Cattin and Wittink (1982), we define relative attribute importance as the range in a consumer's utility estimates for an attribute divided by the sum of ranges across all attributes. Using this definition, it is possible to test whether respondents making conjoint choices differentially focus attention on important attributes, and, additionally, whether the attribute focus effect increases within and across choice tasks.

Greater attention to positive or negative features depending on choice. If a goal is to choose an alternative quickly, then that desire should result in more fixations on

positive features of the chosen alternative. There are three processes that could lead to such a result. Attentional imbalance could come from (1) noncompensatory processing, (2) satisficing heuristics that stop search when an alternative passes an acceptability threshold, or (3) active search for information that confirms a current favorite. We briefly discuss each of these processes next.

Research has shown noncompensatory processing to characterize choices (Gilbride and Allenby 2004). It can take two primary forms in conjoint. People can either screen out alternatives that have an undesired feature or consider only those that have a desired feature. These strategies imply that rejected alternatives are more likely screened out from negative information, whereas chosen alternatives are more likely to be focused on and eventually chosen given positive information.

A threshold model reflects the reasonable desire to stop processing when an alternative is deemed sufficiently attractive—that is, when the processing cost of finding a better option exceeds the expected benefit from that search. Threshold models arise naturally from decision field theory (Busemeyer and Townsend 1993) and have been applied in marketing (Krajbich and Rangel 2011). A satisficing decision rule implies that the threshold is more likely to be passed if the decision maker has recently accessed positive information about the leading alternative. A threshold process thus implies more focus on positive information for chosen compared with rejected alternatives.

Motivated search provides a third way that a respondent might focus more on positive information about a current alternative. Refocusing on information that is known to be positive can lead to faster and more confident choice. The rich literature on search to justify choice (Brownstein 2003) has shown that distortion is most likely when the decision is important, difficult, or emotional.

It is empirically difficult to distinguish between these three ways that conjoint choice could generate greater focus on positive features of chosen alternatives. However, it is reasonable to expect noncompensatory processes to manifest early in the choice process because the goal of cutoffs is to simplify later choice processes. By contrast, because both motivated search and threshold processes relate critically to the final decision, they should be most apparent later in the choice process.

Evidence for Stimulus-Driven Attention and Choice

In contrast to goal-driven attention that arises from enduring values toward alternatives and search, stimulus-driven attention is generated by external conditions that can distort attention and choice. We first consider studies of manipulated attention and then move to attentional shifts that result from the form and location of stimuli in the task.

Manipulated attention. Several empirical studies have shown that manipulated attention alters choice. Armel, Beaumel, and Rangel (2008) alter the duration of attention to pairs of food choices by presenting one decision alternative for 300 milliseconds and the other for 900 milliseconds. They show that alternatives with greater manipulated attention have an increased probability of being chosen. The authors view this result to be consistent with a mere exposure effect, whereby greater attention leads to more positive ratings (Zajonc 1968). Similarly, Janiszewski, Kuo, and Tavassoli (2013) investigate the influence of selective attention and inattention to alternatives on subsequent choices. The authors manipulate the attention that respondents pay to alternatives and show that repeatedly allocating attention to an alternative increases its choice probability.

Another way to manipulate attention is to change the visual saliency among the alternatives presented. Research by Van der Lans, Pieters, and Wedel (2008) shows that the degree to which a brand stands out from its competitors is an important driver of search and has a pervasive effect on consumers' ability to find a desired brand. More generally, studies by Milosavljevic et al. (2012) and Towal, Mormann, and Koch (2013) demonstrate that visual saliency influences stimulus-driven attention and, finally, choices.

When stimulus-driven attentional effects increase the focus on the ultimate choice, a reinforcing causal cycle has been called a "gaze cascade" (Shimojo et al. 2003; Simion and Shimojo 2006). The gaze cascade defines a feedback loop consisting of two reinforcing links: a goal-driven link from preference to attention and a stimulus-driven link from attention to preference. These associations are hypothesized to build on each other to form a cascade that reaches a peak just before the decision. However, recent studies have questioned this explanation of the gaze cascade effect (see Bird, Lauwereyns, and Crawford 2012; Glaholt and Reingold 2009). The current research also questions the stimulus-driven link in a gaze cascade in conjoint choice to the extent that we find little evidence that two stimulus-driven attentional factors, horizontal centrality and the first-fixated alternative (described next), alter choice.

Horizontal centrality. Chandon et al. (2009) demonstrate that the horizontal position of a brand on the shelf positively affects brand choice at the point of purchase. Atalay, Budur, and Rasolofoarison (2012) closely investigate the effect. They replicate respondents' tendency to look at a central alternative initially and demonstrate focus on the central alternative just prior to the decision. They call this latter effect the "central gaze cascade." Valenzuela and Raghubir (2009) argue that the centrality effect in choice may arise because shoppers are accustomed to finding the more desirable offerings in the middle position. If so, attention to the central position may be viewed as stimulus driven, arising from ease of accessibility, or as goal driven, arising from a learned expectation of greater value for centrally placed alternatives. Mormann, Towal, and Koch (2013) quantify the effects of goal- and stimulus-directed attention on consumer choice when consumers choose snack foods from shelves. One of their findings is that centrality increases attention initially for all respondents but has minimal effects on choice. Kreplin, Thoma, and Rodway (2014) demonstrate that a centrality bias in choice is minimized when the choice options are dissimilar from one another. They show that respondents' attention focuses on the central alternative among works of art but that centrality alters choice only when the three alternatives are virtual copies of one another.

These latter results lead us to expect centrality to have less impact on repeated conjoint choice because conjoint emphasizes clearly defined and important features that,

unlike market choices, are independent of alternative position. Put differently, the empirical finding that attractive products are more likely to be found in central shelf positions may not apply for randomly positioned conjoint alternatives.

First-fixated alternative. Reutskaja et al. (2011) examine choices from supermarket shelves under time pressure. They find that respondents look first and more often at items placed in certain regions of the display and are then more likely to choose from those regions. In a recent study (Fisher and Rangel 2014), respondents had to decide whether they would eat a bundle of food items that included a positive and a negative food item after the experiment. Among other results, the authors show that being exposed to the positive food first increases the likelihood of being willing to eat the food bundle. These results suggest that the feature on which participants first fixate might have a stronger influence on choices. Our studies of conjoint choices test whether the first-fixated alternative receives more attention and whether that attention alters choice probabilities. Next, we explore reasons why the results for conjoint choices may diverge from the results discussed in this subsection.

How Conjoint Choices Are Different from Other Choices

Many of the eye-movement studies reviewed in the previous subsection explore single choices for specific alternatives such as faces, snack products, or works of art. By contrast, a conjoint exercise asks people to make choices among alternatives whose multiple features are then shuffled in each succeeding choice task. Conjoint choices further differ in having features that are generally arrayed in a matrix in which attributes are placed in consistent rows. The lattice structure enables respondents to quickly find important attributes and identify promising alternatives.

The layout and repetition of the conjoint tasks are important in terms of the processes available to respondents. In choosing between faces, images, or brands on a shelf, the different features may be interdependent and difficult to compare. Thus, a large mouth may look wrong on a small face, as a high price may look wrong on a small package. In such cases, the value of one feature interacts with the level of another. However, in conjoint, the independent presentation of the alternatives may encourage respondents to simplify their task by ignoring feature interactions. If so, then the value of a conjoint alternative can be expressed as an additive function of the value of its features, and it becomes possible to assess the relationship between value and attention by examining the degree to which attention is associated with a simple model of feature utilities. We propose that these measured values reveal an efficient attentional strategy in conjoint that focuses primarily on attractive alternatives and important attributes.

Focus on attractive alternatives. Increasing focus on the alternative with high expected utility can increase efficiency of conjoint choices. Rather than keeping all information in one's mind, focusing on the leading alternative centers attention on the probability that the current focal option is the best. Thus, demands on memory and cognitive processing are eased as respondents gradually shift attention to the most likely prospect. If this account is correct, it implies a testable inference: alternative focus will increase with practice as respondents learn to identify attractive options.

Focus on important attributes. Attribute focus occurs when attention is drawn to the attributes that are most important to the individual respondent. It is facilitated in conjoint choice tasks in which the attributes have defined, horizontal locations. Therefore, it is relatively easy to learn the locations of the most important attributes and to focus on those attributes with the greatest impact on preferences. If attribute focus helps people make decisions, we can expect it also to increase with experience as respondents learn to identify and locate important attributes.

In summary, we test the following research questions related to attentional focus and search strategies for repeated conjoint choices:

1. To what extent does the focus on each alternative reflect the respondent's utility for the option?
2. To what extent does the focus on each attribute reflect the importance of that attribute to the respondent?
3. How much do attribute and alternative focus change both from progression within the choice task and with experience across choice tasks?
4. Is there evidence of greater attention to positive information for chosen alternatives?
5. Is there evidence that incidental attention distorts choice?

To answer these questions, we examine how people's utilities determine the attentional processes in conjoint choices. A unique feature of conjoint exercises is their ability to generate measures of alternative attractiveness, attribute importance, and feature utility for each choice task. When relating these utility measures to attention, a potential simultaneity problem may arise. In particular, if these utility measures drive fixations, and these fixations in turn drive choices, then the estimated coefficient of the impact of utility on fixations may also capture the relationship between fixations and choice. To circumvent this problem, for each choice task we estimate the utility of each feature using the data from all other choice tasks (e.g., if respondents complete T choice tasks, when estimating the utility function for choice task 3, we use choices from choice tasks 1, 2, 4, 5, ..., T). This ensures that for each choice task, the estimates of feature utility—and thus, alternative attractiveness and attribute importance—are independent of the features of the alternatives in that choice task. Consequently, these holdout estimates enable us to assess the impact of individual utilities on alternative and attribute focus and are statistically unrelated to the specific alternatives chosen in each task.

In the next section, we explore these questions from a relatively model-free perspective using simple bivariate and graphical analyses. These analyses show that conjoint choices become faster and more accurate with practice and give evidence that shifts in attribute and alternative focus are consistent with this greater efficiency. They also show that contextual biases commonly found in other settings are much less salient in conjoint choices. In the following section, we formulate a comprehensive attentional model built around the number of times a respondent accesses each piece of information in the choice task. This analysis allows us to estimate the extent to which respondents focus on attractive alternatives and important attributes both within and across conjoint tasks. Replications then assess

whether our process findings carry over to two other conjoint studies. Finally, we summarize the theoretical and practical implications of our findings for choice-based conjoint.

We present analyses from three different conjoint studies that involve choices among coffee makers, beach vacations, and laptop computers, respectively. We provide an elaborate description of the analysis of the coffee maker study and include less discussion on the other studies because those details are available in Web Appendix A (beach vacation study) and in Yang, Toubia, and De Jong (2015) (laptop study).

EYE-TRACKING EVIDENCE OF PROCESSING OF CONJOINT CHOICES

The coffee maker study sampled regular coffee drinkers at a large European university. Of an initial sample of 110 participants, 60 remained for analysis after we excluded responses with incomplete data resulting from calibration or data-recording problems as well as two participants who chose none of the purchase options in all choice tasks.

The analysis focuses on 12 conjoint choice tasks, each similar to that shown in Figure 1, between three single-cup coffee brewers and a no-choice option. In each task, the 18 features define the six attribute levels for the three alternatives. Study participants learned about the attributes of the displayed products and then made four warm-up practice choices. In addition, we included two other fixed tasks between the random tasks 6 and 7. Although we removed the four warm-up tasks and the two fixed tasks in our analysis, the results differ little if they are included.

The attribute levels of the choice illustrated in Figure 2 come from a total of 20 possible features. Sawtooth Software's (2013) system generated the randomized choice tasks. For each respondent, the choice design is approximately orthogonal across attributes and balanced with respect to the frequencies of the features.

A binocular video-based, head-mounted eye tracker recorded participants' eye movements. The SMI Eye-Link II System (SR Research Inc.) includes two mini cameras

Figure 1

CHOICE TASK FOR COFFEE MAKER STUDY

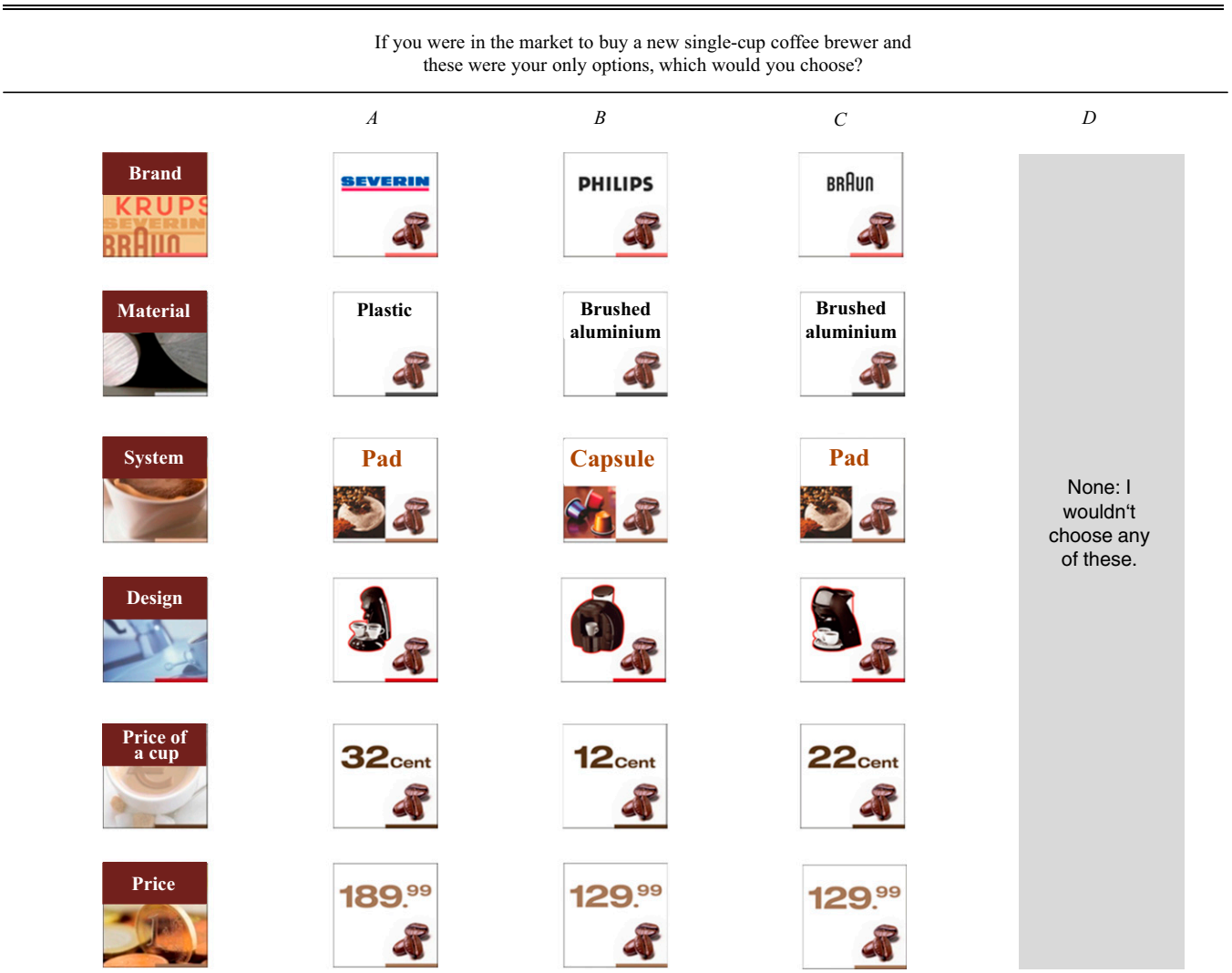
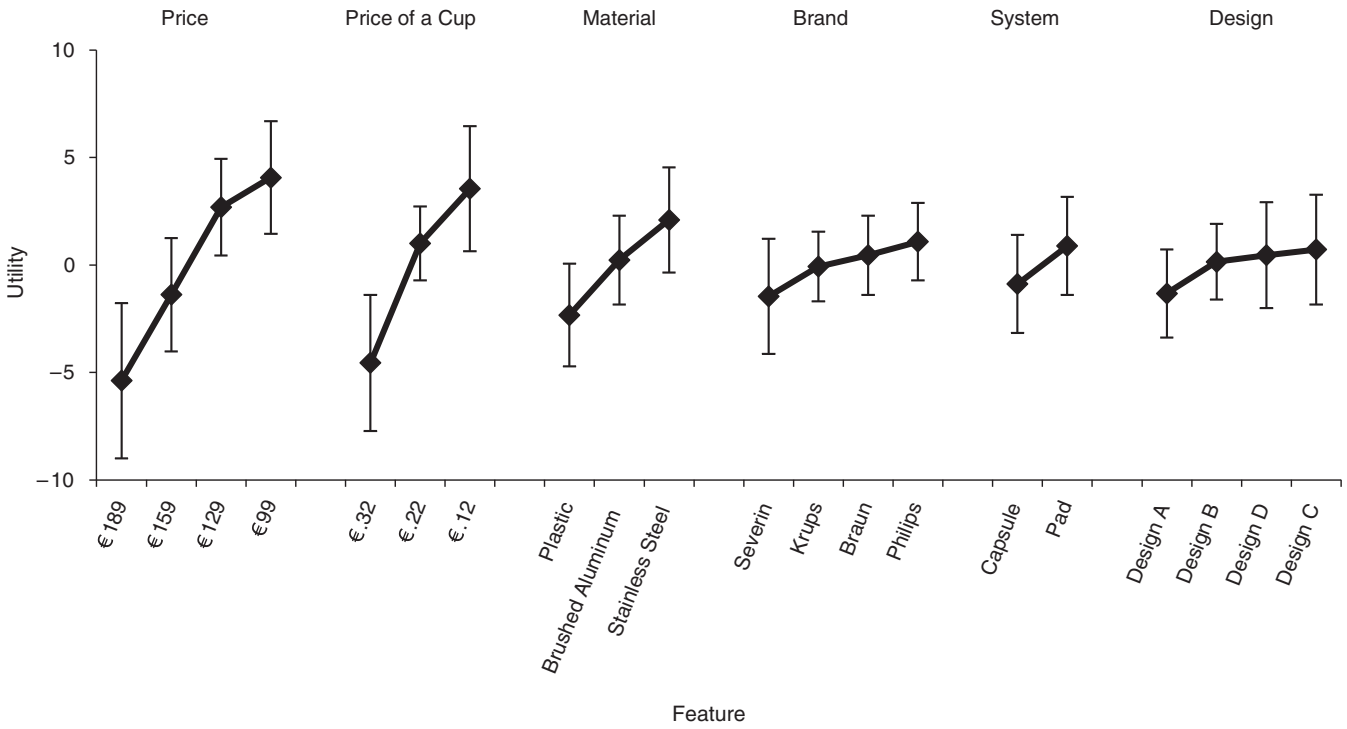


Figure 2
FEATURE UTILITIES WITH STANDARD DEVIATIONS ACROSS RESPONDENTS FOR THE COFFEE MAKER STUDY



that track participants' eye movements. Web Appendix A provides details on the system.

To measure changes in attention through the task, a binary split of the total number of fixations for each choice task differentiates between the first and the second half of the decision process. For the analysis, we focus on the 85% of responses in which subjects chose one of the alternatives shown, but not the no-choice option. Finally, we use the number of fixations as our measure of attention to a feature, although we obtain very similar results from the accumulated amount of time spent on the feature.

Evidence of Increasing Respondent Efficiency and Accuracy

First, we provide evidence that choices across the 12 tasks become more reliable (i.e., more predictable) with practice, despite taking less time to process. Then, we show how alternative and attribute focus also increase with practice and explore the extent to which there are biases in attention or distortions from incidental fixations.

We begin the analysis by estimating the utility for each feature defined by the product-by-attribute grid for each respondent. Web Apppendix B details the Bayesian random-coefficients multinomial logit choice model with normally distributed heterogeneity in consumer coefficients estimated using Markov chain Monte Carlo simulation. Figure 2 displays the means and standard deviations of feature utilities across respondents for the coffee maker study. On average, the price of the unit and the price per cup are the most important attributes. However, the standard deviation bars demonstrate that there are substantial differences across respondents in the importance of attributes, measured by the range in utility within each attribute.

Figure 3 plots average accuracy and number of fixations across the tasks. We estimate the hit rate for each of the 12 tasks by predicting the chosen alternative from the 11 remaining tasks. That process generates an average hit rate of 68% correct predictions across the three purchase options and the no-purchase option. More importantly, the hit rate improves over time by approximately 12 percentage points

Figure 3
HIT RATE INCREASES AND DECISION TIME DECREASES WITH EXPERIENCE FOR THE COFFEE MAKER STUDY

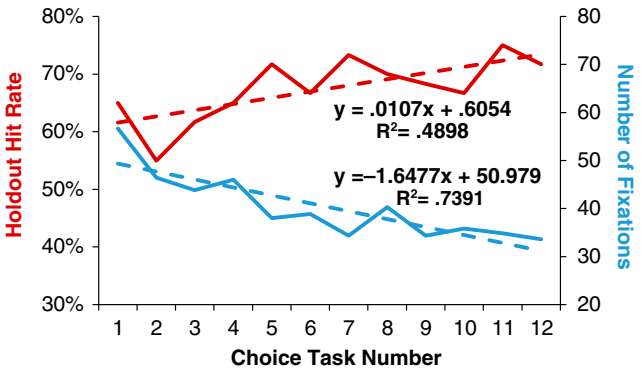
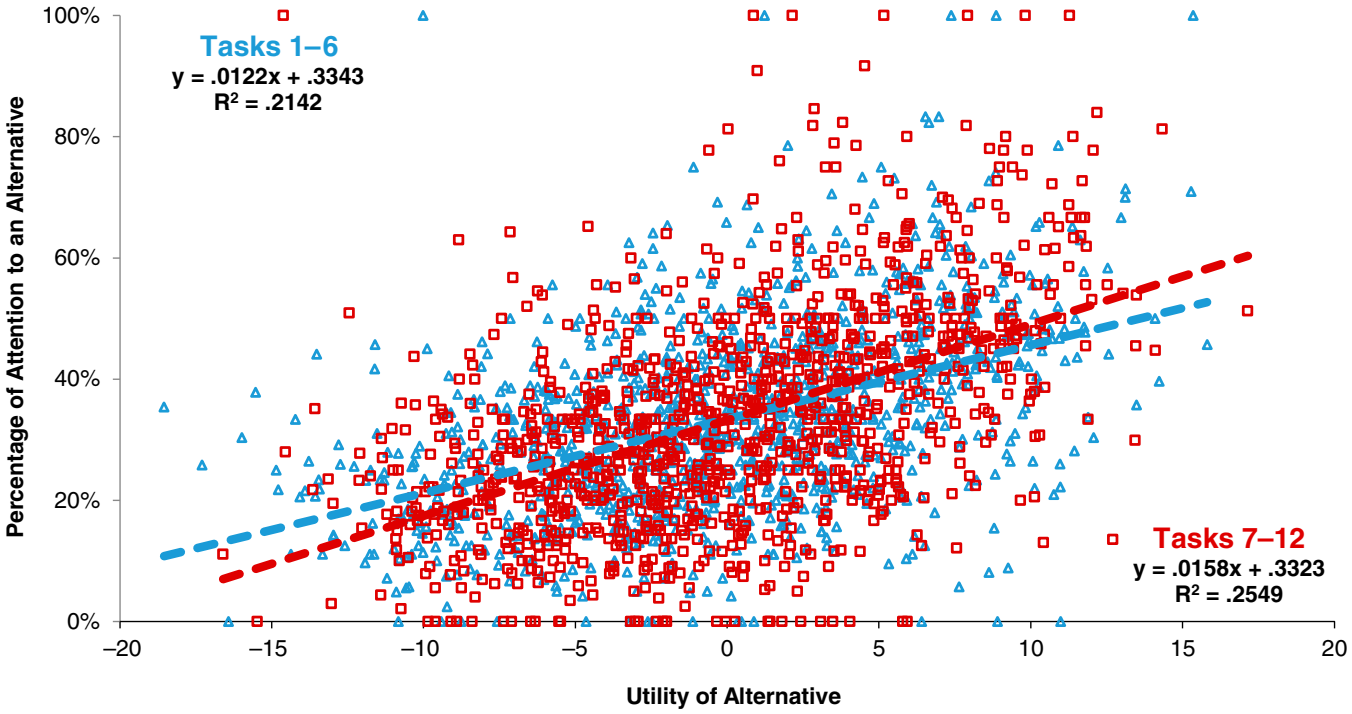


Figure 4

ATTENTION TO AN ALTERNATIVE INCREASES WITH THE ATTRACTIVENESS OF THE ALTERNATIVE, AND THIS RELATIONSHIP INCREASES WITH PRACTICE



(B = 1.07, t = 3.099, p = .011). Concurrently, the number of fixations decreases from 50 fixations to approximately 32 fixations (B = −1.651, t = 6.271, p < .01). A similar graph replacing fixations with total task duration in seconds shows a drop in task completion time from 18 to 12 seconds with practice. Johnson and Orme (1996) demonstrate very similar shifts in decision time and accuracy in a meta-analysis of several commercial conjoint projects. We interpret Figure 3 as evidence that repeated conjoint tasks result in less effortful but more accurate choices and propose that alternative and attribute focus contribute to this efficiency gain.

Evidence for Increasing Focus on Attractive Alternatives

In Figure 4, we investigate alternative focus by considering the probability of fixating on an alternative as a function of its estimated utility. Combining the measures for 60 respondents on each of 12 tasks and 3 alternatives, then taking out the 15% who chose the no-purchase option, results in a total of 1,833 observations. The graphs show that alternatives with higher total utilities generate more attention, whereas those with lower total utilities generate less attention. They also show that the focus on high-utility alternatives increases with practice. The slope for the first six tasks (B = .012) is significantly smaller than that for the last six tasks (B_{diff} = .016, t = 3.321, p < .01), and they are both significantly different from zero (p < .01).

The focus on attractive alternatives is not surprising and is consistent with research discussed previously showing that the chosen alternative receives more attention. Furthermore, the finding that alternative focus increases with practice is consistent with the finding that efficiency gradually develops with choice experience.

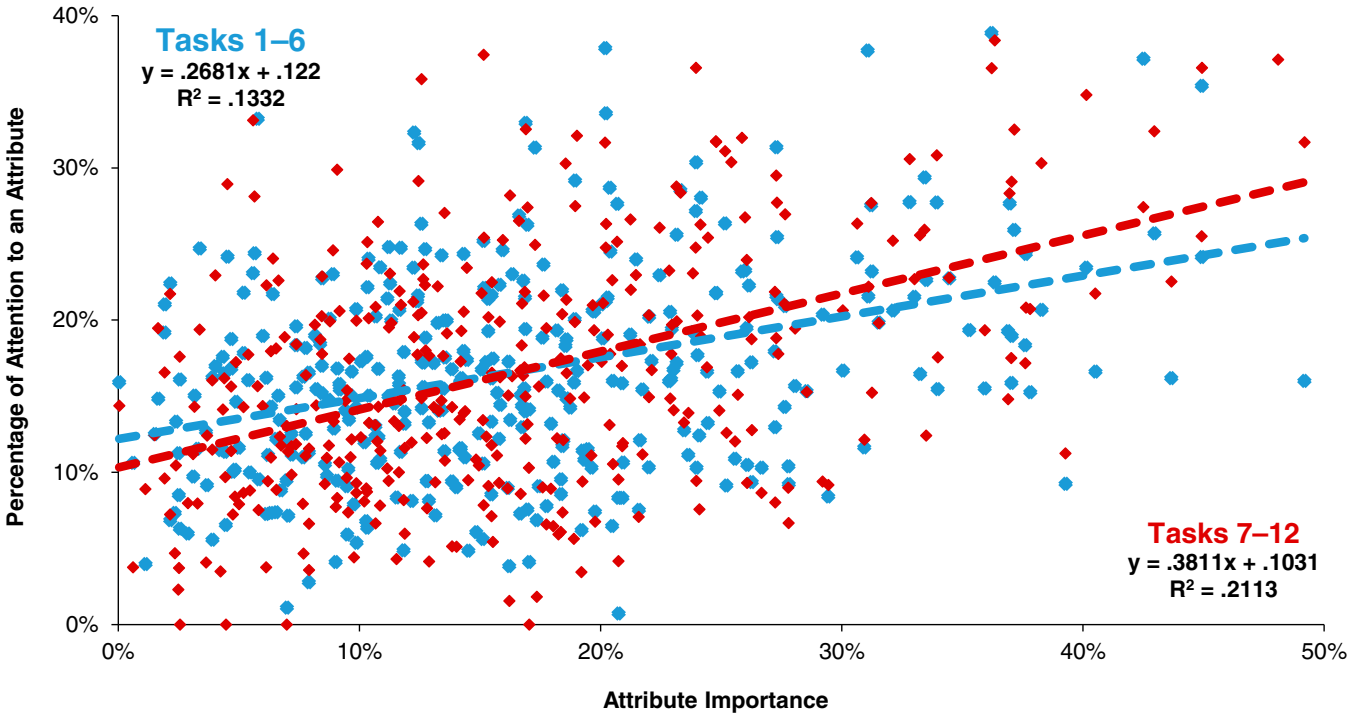
Evidence for Increasing Focus on Important Attributes

Attribute focus occurs to the extent to which the frequency of fixating on an attribute depends on its importance. Individual attribute importance is measured in the standard way, by taking the utility range of each attribute and dividing that by the sum of the utility ranges across all attributes (in line with Cattin and Wittink 1982). Combining the measures for 60 respondents on each of 6 attributes results in 360 observations. Figure 5 shows that attributes with greater importance to respondents generate greater attention overall and that attribute focus increases with practice, but this increase is not significant (t = 1.082, p = .28).

Evidence for Biased Attention Depending on Choice

Because people focus attention on attractive alternatives, it makes sense that features with high utility that are connected with the chosen alternative receive more attention. However, it is worthwhile to question whether there is a bias toward high-utility features of chosen alternatives. As we have discussed, such a bias could be evidence of (1) a screening rule that shifts focus away from other alternatives on the basis of an undesired feature, (2) a threshold choice model that makes the choice of an alternative more likely as a result of focus on its desired

Figure 5
ATTENTION TO ATTRIBUTES INCREASES FOR IMPORTANT ATTRIBUTES BUT IS NOT SIGNIFICANTLY HIGHER WITH PRACTICE



features, or (3) a motivated search that drives attention toward evidence that justifies the current option.

Figure 6 displays the percentage of attention to a feature within an alternative against the standardized relative utility of a feature within an alternative. For chosen alternatives, there is a greater tendency to focus on more positive features (B = .011, t = 3.256, $p < .01$), but the reverse occurs for rejected alternatives (B = −.005, t = −1.595, p = .111). Thus, a one-standard-deviation shift in a feature's relative utility increases attention across the six features of an alternative by .011/.166 = 6.7% for a chosen alternative but decreases it by .0054/.166 = 3.2% for rejected alternatives.

Given that there are three well-established processes that generate greater attention to positive features of chosen alternatives, the relative weakness of the effect is surprising, particularly when compared with the strong impact of attractive attributes and important attributes. We reexamine this finding using a more general model of cell attention.

Evidence That Incidental Fixations Distort Choice

The preceding analysis is consistent with goal-driven attention, in which focusing on attractive alternatives and important attributes simplifies the choice process that can in turn increase the efficiency and accuracy of choice. In this subsection, we examine the impact of attention that stems from the centrality of the choice or the identity of the first alternative viewed.

First, consider centrality. With three alternatives, it is reasonable that the one in the center receives more fixations simply because it is visually in the way as respondents work to determine their choice. Figure 7 displays the proportion of respondents fixating on the left, middle, or right alternative in 20-millisecond intervals within a choice task. Attention is initially equally directed to the alternatives on the left and center but gradually shifts toward the right. A simple linear trend is significant and negative for the left alternative ($B_l = -.45$, $p < .01$), significant and positive for the right alternative ($B_r = .26$, $p < .01$), and significant and positive for the middle alternative ($B_m = .34$, $p < .01$). In all, the middle alternative, because of its location, receives approximately 21% more attention than those on the left or the right.

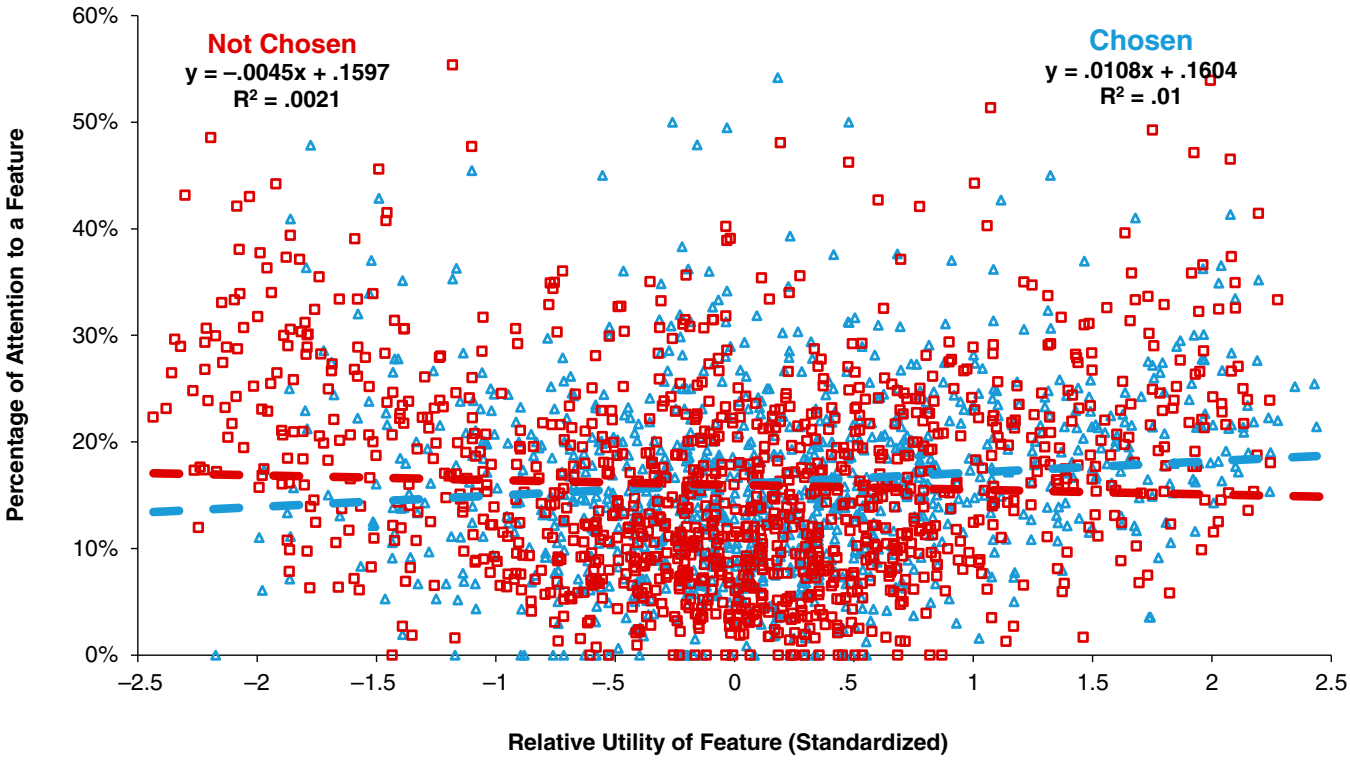
The tendency to look more at the center of a computer screen is well known. Vision researchers have investigated the central-fixation-bias effect and have suggested several different possible explanations, ranging from the notion that the center is a convenient location from which to start oculomotor exploration to the suggestion that people have a tendency to recenter the eyeballs in their sockets (Tatler 2007). We more closely investigate the central-fixation-bias effect for our data in Table 1 and Web Appendix C.

Here, we focus on the extent to which this incidental attention affects choice. If the additional attention garnered by the middle alternative generates greater preference for it, this should result in greater choice of the middle alternative. Middle alternatives receive 34% of choices versus the corresponding 33% for either the left or right alternatives. The coefficient for centrality predicting choice in a logit model is not significant (B = .0159, t = .37, p = .71).

Thus, we find evidence that centrality generates attention but not choice. This result contrasts with the findings of Atalay, Budur, and Rasolofoarison (2012), in which, in a nonconjoint context, the middle alternative generated both more fixations

Figure 6

ATTENTION TO FEATURES INCREASES WITH GREATER UTILITY FOR CHOSEN ALTERNATIVES BUT DECREASES FOR REJECTED ALTERNATIVES



and more choices. Two factors might account for the differences in our results. First, it is possible that our conjoint warm-up exercises made the centrality link found in simulated shelves less applicable. Second, the difference between the conjoint and a simulated store choice may have lessened any expectation of the middle option being better.

The second test for the influence of stimulus-driven attention on choice uses the first alternative. Because each new task randomly scrambles the assignment of features to alternatives, the respondent has no control over features revealed in the first exposure. Thus, it is possible to observe whether that unplanned exposure alters choice probabilities. The alternative examined first averages 15.14 fixations, compared with 13.13 fixations for the other alternatives. This 15% difference is strongly significant ($t = 3.881$, $p < .01$). However, the first exposure generates 36.5% of the choices, compared with 31.75% for the other two alternatives. This 14% difference is not significant ($B = .139$, $t = 1.130$, $p = .257$) when tested using a logit choice model.

Summary

These results are important because they identify simple processes that enable conjoint respondents to perform a difficult task efficiently. Respondents differentially attend more to attractive alternatives and important attributes, and this focus increases with practice. In terms of search biases, there is evidence that respondents focus only slightly more on positive features of chosen alternatives and negative features of rejected alternatives. Finally, there is little evidence that the 21% more fixations on the middle alternative alter choice or that the 15% more fixations on the alternative first examined increase choice.

In all, these results demonstrate that respondents making repeated conjoint choices focus on the information that is most relevant to make a decision. That result is consistent with Rehder and Hoffman's (2005) support for a goal-driven account whereby values drive attention. Had a stimulus-driven account been operating, we would have expected greater impact of initial attention in the choice process and a positive effect from incidental fixations, neither of which occurred.

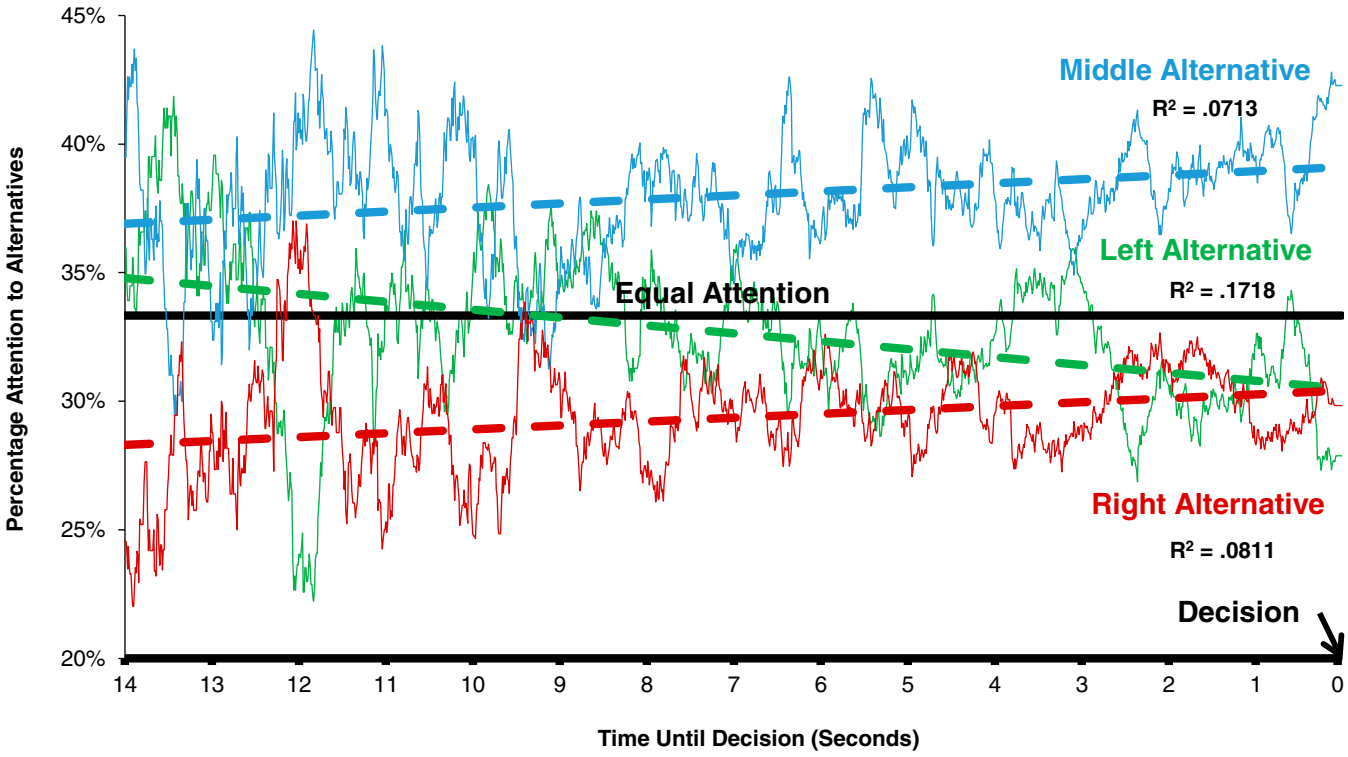
The next section presents a hierarchical model predicting fixations on each of the cells presented to subjects in each choice task. It provides a more powerful account of attentional processing strategies, examining the joint impact of alternative attractiveness, attribute importance, and feature utility both within and across tasks. Furthermore, the model controls for other factors that influence attention, such as the effect of alternative position, the identity of the first-examined alternative, and the difficulty of the choice task.

A GENERAL MODEL OF CELL ATTENTION

An integrated model of attention in each task derives from the count of fixations each respondent makes on the 18 cells in the 3 × 6 attribute choice grid shown in Figure 1. A Poisson count model with a log-link function is appropriate because it assumes that the expected frequency of attending

Figure 7

SHIFT IN FIXATIONS ON LEFT, RIGHT, AND MIDDLE ALTERNATIVES AS DECISION APPROACHES



to a cell shifts proportionately depending on the characteristics of the cell. These characteristics are the attractiveness of the alternative, the importance of the attribute, and the utility of the feature. By also including whether the counts occurred for the first or second half of fixations for each choice, it is possible to assess the degree to which these characteristics shift within a task. Similarly, by dividing the task into the first and second group of six tasks, we can assess the degree to which fixations shift with practice. Finally, this analysis enables us to control for individual differences; task number; whether the cell is central or associated with the first alternative examined; and choice task difficulty, operationalized by the entropy, $\sum_j P_j(\ln P_j)$, of the respondent's predicted choice probabilities (P_j).

There are 25,920 observations corresponding to 60 respondents, 12 tasks per respondent, 18 cells per task, and 2 halves for each task. These observations are not independent, so the model accounts with random coefficients for respondents at the highest level and then tasks at the second level.

Table 1

FIXATIONS AND CHOICES BY HORIZONTAL POSITION OF COFFEE MAKERS

	Left Alternative	*Middle Alternative*	*Right Alternative*
Percentage of fixations	33.1% (.022)	37.5% (.020)	29.4% (.026)
Percentage chosen	32.6% (.055)	34.0% (.066)	33.4% (.083)

Notes: Standard errors are in parentheses.

Formally, Equation 1 assumes a multilevel Poisson model of cell fixations:

$$y_{ijkth} \sim \text{Poisson}(\lambda_{ijkth}), \text{ with} \tag{1}$$

$$\ln \lambda_{ijkth} = \alpha_i + \beta_{t(i)} + \gamma_h + \delta X_{ijkth}, \tag{2}$$

where y_{ijkth} in Equation 1 is the number of fixations from participant i to attribute k belonging to alternative j during half h of choice task t. As described previously, y_{ijkth} follows a Poisson distribution governed by the parameter λ_{ijkth}. This parameter is in turn modeled using a log-linear link function in Equation 2 characterized by the following terms:

- α_i = participant random effects, which are normally distributed and control for systematic variance in fixations across subjects;
- $\beta_{t(i)}$ = task-within-participant nested random effects, which are also normally distributed and control for systematic variance in fixations across tasks from the same subject;
- γ_h = task-half fixed effect;
- X_{ijkth} = a vector of characteristics of cell (j, k) for participant i in half h belonging to choice task t; and
- δ = the corresponding vector of coefficients for X_{ijkth}.

We then estimate the model parameters via maximum likelihood, although a Bayesian estimation yields almost identical results.

To facilitate interpretation, we standardize the four continuous measures of alternative attractiveness, attribute

Table 2
MULTILEVEL ANALYSIS OF FACTORS INFLUENCING FIXATIONS IN THREE STUDIES

	Coffee Maker Study		*Beach Vacation Study*		*Laptop Study*	
Model Term	*% Change*	*Significance*	*% Change*	*Significance*	*% Change*	*Significance*
Alternative attractiveness	+40.9%[a]	t = 35.441, $p < .01$	+33.2%	t = 31.112, $p < .01$	+49.4%	t = 80.181, $p < .01$
Alternative attractiveness × Task progression	+12.6%	t = 9.214, $p < .01$	+39.0%	t = 18.952, $p < .01$	+29.4%	t = 28.858, $p < .01$
Alternative attractiveness × Task experience	+12.3%	t = 6.362, $p < .01$	+8.7%	t = 4.590, $p < .01$	+9.9%	t = 9.489, $p < .01$
Attribute importance	+25.4%	t = 40.867, $p < .01$	+16.4%	t = 20.454, $p < .01$	+37.1%	t = 94.905, $p < .01$
Attribute importance × Task progression	+15.7%	t = 13.384, $p < .01$	−3.8%	t = −2.647, $p < .01$	−26.7%	t = −47.706, $p < .01$
Attribute importance × Task experience	+6.2%	t = 5.478, $p < .01$	+5.8%	t = 3.828, $p < .01$	+5.6%	t = 8.357, $p < .01$
Feature utility	−2.8%	t = −4.777, $p < .01$	−1.2%	t = −1.495, $p = .135$	−5.7%	t = −16.644, $p < .01$
Feature utility × Task progression	0%	t = −.023, $p = .981$	−4.2%	t = −2.787, $p < .01$	−3.5%	t = −5.173, $p < .01$
Feature utility × Task experience	−2.4%	t = −2.100, $p = .036$	−3.5%	t = −2.310, $p = .021$	−2.8%	t = −4.097, $p < .01$
Task progression	−5.2%	t = −4.395, $p < .01$	−6.6%	t = −4.361, $p < .01$	+4.9%	t = 6.147, $p < .01$
Task experience	−23.7%	t = −8.035, $p < .01$	−25.5%	t = −5.582, $p < .01$	−3.4%	t = −11.044, $p < .01$
Horizontal centrality	+9.5%	t = 14.753, $p < .01$	+7.6%	t = 8.674, $p < .01$	+18.8%	t = 46.798, $p < .01$
First-fixated alternative	+13.5%	t = 9.536, $p < .01$	+25.6%	t = 12.335, $p < .01$	+16.7%	t = 19.195, $p < .01$
Task difficulty	+6.1%	t = 3.316, $p < .01$	+2.2%	t = .781, $p = .435$	+4.9%	t = 3.901, $p < .01$

[a]In other words, a one-standard-deviation shift in the attractiveness of an alternative increases the number of fixations by 40.9%.

importance, feature utility, and task difficulty. We also zero-center the four categorical variables of task progression, task experience, horizontal centrality, and the first-examined alternative. Table 2 provides the multilevel results across the three studies. Here, we focus on the column that provides percentage change in fixations on a particular cell and the associated t-tests for the coffee maker study. We derived the former by exponentiation of the raw Poisson coefficients (provided in Web Appendix C).

The first row for the coffee maker study indicates that a unit change in the standardized utility of the alternative generates a 40.9% increase in the number of fixations when all other cell characteristics are at their mean levels. The second row shows that this increase in the expected number of fixations is stronger as one moves from the first to the second half of the fixations. The estimate for the first half is a $1.409 \times e^{-.119/2} - 1 = 32.8\%$ increase in fixations, with an increase of one standardized unit of alternative utility. By contrast, in the second half there is a $1.409 \times e^{.119/2} - 1 = 49.5\%$ increase. These results provide a multivariate replication of the bivariate analyses shown previously and demonstrate substantial impact of alternative attractiveness on feature attention that increases both within and across tasks. The effects for attributes also replicate the bivariate analyses. Important attributes generate more fixations that increase with practice and within the task. This latter result suggests that respondents shift their attention to trading off differences among important attributes rather than examining the value of less important attributes.

Feature utility has reliable but modest effects. Although we did not hypothesize the significant negative effects of feature utility and its expansion across tasks, these effects may be important. A positive coefficient would suggest that respondents search for positive information to justify choice. Thus, a negative coefficient provides additional evidence against biased exposure to positive features of the chosen alternative. However, it is important to note that this negative coefficient for the impact of feature utility on attention is only significant when alternative attractiveness is included in the model. The simple correlation between feature utility and alternative attractiveness is r = .40. Taken together, this analysis suggests that respondents attend more to the alternatives with positive features, but within alternatives they focus more heavily on relatively negative features.

It is instructive to comment briefly on the control variables shown in Table 4. As we have noted, both the central and the first-examined alternative generate significantly greater attention. Furthermore, the finding that fixations are 24% less likely in the last six tasks corresponds roughly with the drop in the number of fixations with practice, shown in Figure 3. The greater number of fixations for choice tasks with higher entropy means that respondents appropriately spend more time and attention on difficult choices in which the utilities of different alternatives are closer together. This result is consistent with Fisher and Rangel's (2014) finding that utility-balanced bundles take more processing time and generate a higher number of fixations.

The dominant effects of alternative attractiveness and attribute importance offer a reasonable description of the way respondents process conjoint choices. The early fixations focus moderately on attractive alternatives and important attributes. However, as choice progresses, both alternative and attribute focus increase strongly. This finding makes sense if respondents broadly scan the matrix in the first half of each task. However, as the decision approaches, attention gravitates toward the important aspects of likely choices.

The lack of measurable contextual biases in this conjoint study contrasts with the relatively strong process evidence of fixations focused on attractive alternatives and important attributes. Because these effects are surprising, it is important to replicate the results to determine whether they are study specific.

TWO CONCEPTUAL REPLICATIONS

The replications come from eye tracking in conjoint studies that are deliberately different from the coffee maker study. The first replication is a conjoint study of beach vacations detailed in Web Appendix A. The second replication is a conjoint study of laptops from Yang, Toubia,

Table 3
DIFFERENCES BETWEEN THE THREE EYE-TRACKING CONJOINT STUDIES

Study	*Coffee Maker*	*Beach Vacation*	*Laptop*
Student respondents	60 Europeans	35 Australians	70 Europeans
Number of alternatives	3 and a "none" option	5	4
Number of distinct features	20	18	24
Number of choice tasks	12	8	20
Design within choice tasks	Randomized	Randomized	Fixed across subjects
Design within subjects	Orthogonal and level balanced	Orthogonal and level balanced	Totally random
Incentive compatible	No	No	Yes
Data conducted by	Authors of this article	Authors of this article	Yang, Toubia, and De Jong (2015)

and De Jong (2015). We thank the authors for making these data available.

Table 3 provides a summary of the important differences across the studies. They differ with respect to the product category: coffee makers and laptops are relatively utilitarian durables, whereas beach vacations reflect short-term hedonic experiences. The number of alternatives per choice shifts from three to four or five, and the number of distinct features varies from 18 to 24. The designs also differ. Both the coffee maker and the beach vacation studies use Sawtooth Software's (2013) randomized design on 12 and 8 tasks, respectively. The laptop study employs a random design across 20 tasks, but all respondents saw the same choice sets in the same order. Finally, the laptop conjoint is incentive aligned in that respondents had a chance to win the laptops they chose.

Figures 8 and 9 display the means and standard deviations of the feature utilities for the two replication studies (laptops and beach vacation studies). Table 4 gives the measures of efficiency and bias for all three studies. In the replication studies, a strongly significant drop in the number of fixations with practice varies from 25% for the laptop study to nearly 50% for the vacation study. Accuracy, measured as the probability of correctly predicting

Figure 8
FEATURE UTILITIES WITH STANDARD DEVIATIONS ACROSS RESPONDENTS FOR THE BEACH VACATION STUDY

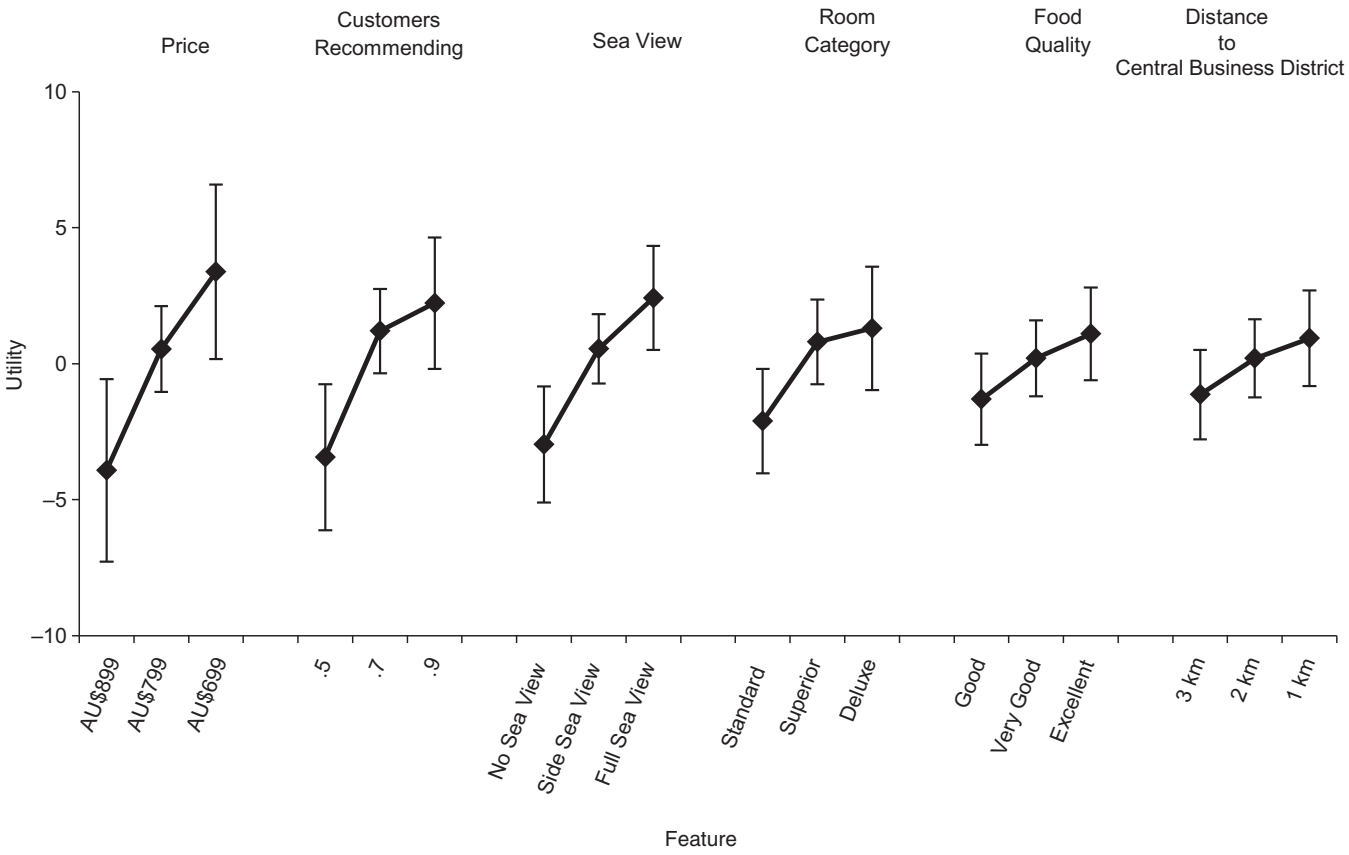
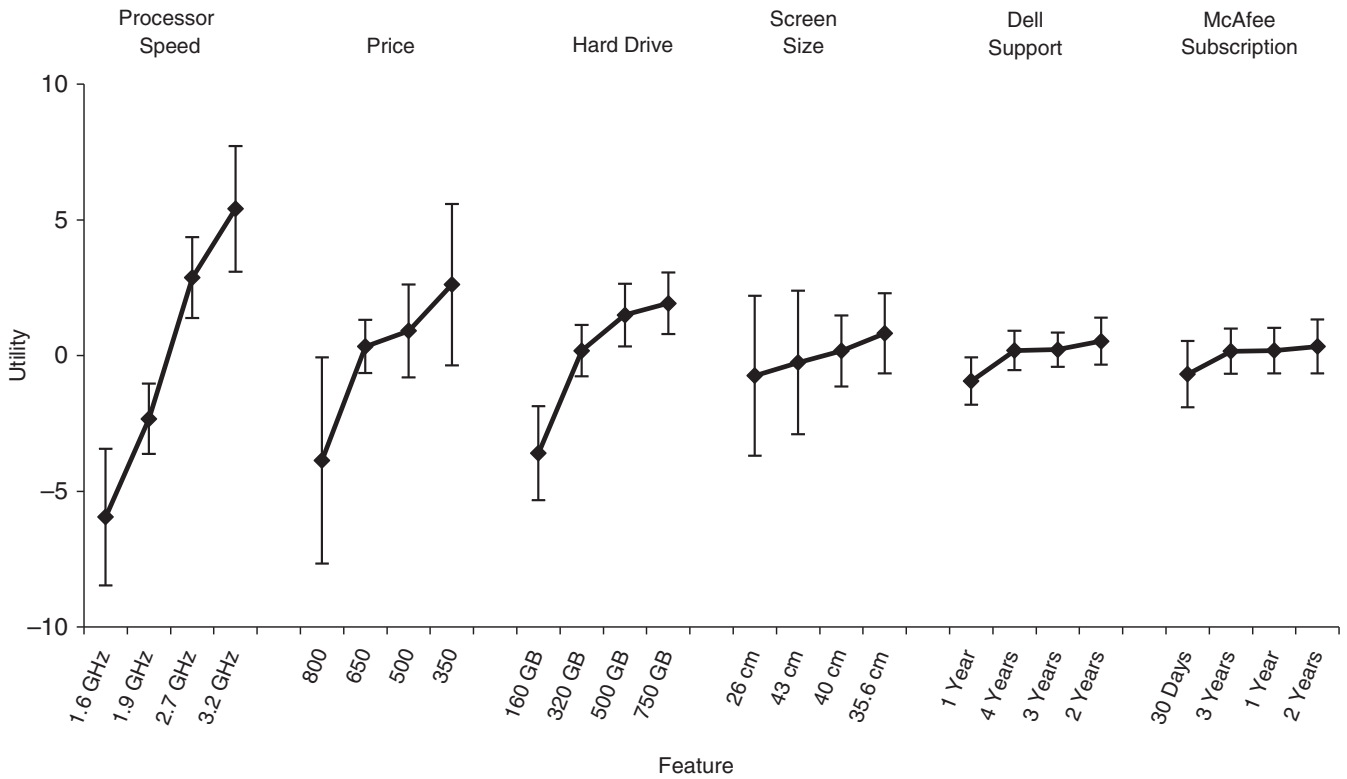


Figure 9
FEATURE UTILITIES WITH STANDARD DEVIATIONS ACROSS RESPONDENTS FOR THE LAPTOP STUDY



holdout choices, increases by approximately 15% across the three studies. However, that increase is not statistically significant for the beach vacation study.

Incidental fixations from either the first-focused-on alternative or the central alternative demonstrate strongly consistent shifts in attention that vary from 16% to 38%. Except for centrality in the laptop study, the shift in choice is nonsignificant. Thus, across studies we find that the first-fixated-on alternative and the central alternative have a large impact on attention but relatively little impact on choice. Note that when estimating the influence of centrality in the laptop study, we contrast the three alternatives in the center and the two alternatives at the edges, but results do not change substantially with different definitions of centrality. We provide detailed centrality statistics in Tables A1 and A2 in Web Appendix C.

Table 4 also examines whether there is a bias toward attention to positive features for chosen alternatives. The results are remarkably consistent across the three studies. Respondents are more likely to focus on positive features over negative features of the chosen alternatives. However, this expected effect, while reliable, is relatively small compared with focus on the first-fixated-on or central alternatives.

Table 2 summarizes the percentage changes in attention from the multilevel analysis of attention across studies. The average utilities for beach vacations and laptop computers are given in Figures 8 and 9, respectively. Details and the raw statistics for those analyses appear in Table A3 in Web Appendix C. It is useful to note areas that replicate across the three studies and to highlight a few surprising and potentially relevant shifts. The attractiveness of alternatives consistently drives fixations. A one-standard-deviation shift in the utility of an alternative increases fixations by 33%–49%. Furthermore, in all cases, that shift increases by 13%–39% within task and by approximately 10% across tasks. The importance of attributes also has consistent impact on fixations but less impact on fixations than alternative focus. That relationship also increases across tasks by approximately 6%.

The studies differ from the initial study with respect to the change with task progression of fixations on important attributes. For the coffee maker study, attention increases by 15% in the second half of fixations within a task, whereas for the beach vacation and laptop studies, attention to important attributes drops by 4% and 27%, respectively. That negative shift in the second half of fixations implies that respondents examine attributes that are less important closer to choice. The substantial shift to less-important attributes is reasonable in the case of the incentive-compatible laptop study. Before making a final decision, respondents appear to be moved to check the less-important attributes.

The other aspects of attention are remarkably consistent across studies. The multilevel model confirms that the number of fixations drops with practice and that fixations are more prevalent for first-fixated and centrally located alternatives.

Table 4
MEASURES OF EFFICIENCY AND ATTENTIONAL BIASES ACROSS THE THREE STUDIES

	Coffee Maker Study		*Beach Vacation Study*		*Laptop Study*	
Effect	*% Change*	*Significance*	*% Change*	*Significance*	*% Change*	*Significance*
Efficiency						
Drop in number of fixations with practice	−36%	t = 6.271, $p < .01$; n = 720	−48%	t = 5.745, $p < .01$; n = 304	−25%	t = 5.647, $p < .01$; n = 1,400
Gain in accuracy with practice	+19%	t = 3.099, $p = .011$; n = 611	+18%	t = 1.383, $p = .168$; n = 304	+14%	t = 2.214, $p = .027$; n = 1,400
Incidental Fixations: Attentional Distortion to First Alternative Accessed						
Focus on first-accessed alternative	+15%	t = 3.881, $p < .01$; n = 1,833	+29%	t = 4.604, $p < .01$; n = 1,520	+16%	t = 5.986, $p < .01$; n = 5,600
Greater choice for first-accessed alternative	+14%	t = 1.130, $p = .257$; n = 1,833	−4%	t = .140, $p = .892$; n = 1,520	−11%	t = .005, $p = .957$; n = 5,600
Incidental Fixations: Attentional Distortion to Alternatives in the Center of the Choice Set						
Focus on central alternatives	+21%	t = 5.302, $p < .01$; n = 1,833	+24%	t = 4.370, $p < .01$; n = 1,520	+38%	t = 14.503, $p < .01$; n = 5,600
Greater choice for central alternative	+3%	t = .670, $p = .506$; n = 1,833	+11%	t = .580, $p = .563$; n = 1,520	+14.3%	t = 4.450, $p < .01$; n = 5,600
Change in Attention from an Increase in Standardized Feature Utility Depending On…						
…the chosen alternative	7%	t = 3.256, $p < .01$; n = 1,200	4%	t = 2.119, $p = .034$; n = 684	7%	t = 5.060, p < .01; n = 1,680
…the rejected alternative	−3%	t = −1.595, $p = .111$; n = 1,200	−6%	t = −2.388, $p = .017$; n = 684	−16%	t = −7.707, $p < .01$; n = 1,680

Greater task difficulty, measured by the entropy of the choice task, increases the number of fixations, as we would expect. Furthermore, in all studies, both attribute and alternative focus increase with practice, a result consistent with greater speed and accuracy occurring at the same time.

ROBUSTNESS ASSESSMENT

Several robustness checks confirm the stability of our results across all three studies. These checks include using a negative binomial (NB) model instead of the Poisson model (i.e., allowing for over-dispersion of the fixation data) and fitting a linear model of cell fixations. In addition, we also considered the use of fixed instead of random effects to control for subject and task differences (detailed results are available from the authors on request). Considering the base model (Poisson), the NB model, and the Poisson model with fixed effects, these three specifications yield very similar results. In particular, the impact of the alternative attractiveness and attribute importance are verified under these three variants of the cell-fixation model. The interactions between these effects and (1) task progression and (2) task experience also replicate, although a few interactions became marginally significant. Finally, a linear specification yields an inferior fit compared with the Poisson and NB models, in which fit is assessed on the basis of the Akaike and Bayesian information criteria. This suggests that the impacts of the cell characteristics (e.g., alternative attractiveness on cell fixations) are more consistent with a multiplicative than an additive model. Nevertheless, under the linear model we still obtain significant alternative attractiveness and attribute importance effects, although feature utility and some of the interactions are no longer significant.

GENERAL DISCUSSION

Overall, these results point to critical differences between the process of repeated conjoint tasks and individual choices. In contrast to the latter, the features of conjoint alternatives randomly shift with each task, thus emphasizing the evaluation of independent attributes. Our results support the idea that attention predominately follows alternative attractiveness and attribute importance and, furthermore, that there is very little evidence of stimulus-driven attention or susceptibility to incidental fixations altering choice.

It is important to note the role that repetition in conjoint choices plays in our ability to derive these results. Repetition allows us to estimate alternative attractiveness, attribute importance, and feature utility for each choice independent of the attention data for that choice task. Although there are programming and computational costs in estimating different preference structures for each task, these holdout estimates are important for our results. Across studies, instead of correctly predicting approximately 60% of the holdout choices, the Bayesian model that pools all choice tasks has an internal hit rate of approximately 85%, indicating substantial overfitting unless holdout estimates are used.

The three studies reveal a conjoint choice process in which respondents learn to be more efficient and effective in their choices by focusing on attractive alternatives and important attributes. They also portray a process that has limited distortion arising from greater attention to positive features of chosen alternatives or from incidental fixations. In the following subsections, we summarize four major results.

Result 1: Alternative Focus Directs Attention to Options with High Utility

To simplify the task of verifying the best option, conjoint respondents focus on attractive alternatives. This alternative focus increases within and across tasks with practice. We expected the growth within tasks, which parallels the

findings of a greater alternative focus on chosen alternatives as choices approach. The increase across tasks suggests that respondents in conjoint exercises develop skills in quickly finding and identifying good options.

Previous studies have shown that attention to alternatives is a good predictor of brand choice (see, e.g., Lohse and Johnson 1996; Pieters and Warlop 1999; Russo and Leclerc 1994). In showing that the utility of an alternative is a good predictor of attention, our results are consistent with those findings and suggest a process through which alternative focus helps generate efficient and reliable conjoint choices.

Result 2: Attribute Focus Directs Attention to Important Attributes

To increase the likelihood that information reviewed will influence choice, people making conjoint choices focus differentially on important attributes. Focus on important attributes increases with practice in all cases, consistent with a gradual increase in the ability to identify and find important information relevant to the choice.

Attribute focus increased within a task for the coffee maker study, slightly but significantly decreased for the beach vacation study, and decreased strongly for the laptop computer study. The relative decrease in attribute importance for the laptop study implies a shift to less-important attributes as the decision approaches. Two factors might make such a processing strategy likely for the laptop study. First, as Figure 9 illustrates, three attributes dominate: processor speed, price, and hard drive. These three attributes may initially be used to identify important candidates, whereas less-important attributes would be used later to resolve ties. Second, the laptop study is unique in being incentive compatible. Consumers can be expected to look more deeply into all attributes, including less-important ones, to confirm their decision just before making a consequential choice.

Result 3: After We Account for Alternative Attractiveness and Attribute Importance, Feature Utility Has a Minor Impact on Attention

Univariate analysis of feature utility indicates that it has a positive impact on attention. However, accounting for attribute importance and alternative attractiveness makes the impact of feature utility negative and an order of magnitude smaller than the impact of alternative attractiveness or attribute importance. This is a surprising result because it is reasonable to expect that features about which respondents care deeply would have a strong impact on attention and choice. However, from a processing perspective, focusing on attribute importance or alternative attractiveness simplifies the question of where to place attention. That ease-of-processing account agrees with the finding that, with experience, both attribute importance and alternative attractiveness increase, whereas net feature utility becomes consistently more negative.

This dominance of attributes and alternatives in conjoint choices may not carry over to marketplace decisions. In conjoint, the ranges of the attributes are fixed, meaning that across choice sets the importance of attributes is relatively constant. In addition, the features reflected in attribute levels are constant and repeated. Thus, in conjoint there are relatively few surprises in terms of shifts in attribute ranges or the particular features. By contrast, for single or less structured choices, attribute ranges can differ greatly, thus limiting the usefulness of prior expectations of attribute importance. Furthermore, choices in the marketplace abound with surprising, salient, and important features, as we observe when special discounts are made salient using colored displays. In such a context, unique features appropriately have a stronger impact on attention and choice. By contrast, the background stability and repetition of the conjoint choice tasks generates a core utility structure that is relatively stable and less exposed to common context effects.

We also examined whether patterns of search for chosen alternatives lead to more fixations on positive over negative features. We found a significant but relatively small effect in the bivariate analyses and validated it when adjusting for numerous covariates in the multilevel analysis. Overall, these analyses indicate that negative features receive more attention and that this negativity effect is significantly greater for rejected than for chosen alternatives. This result raises the question of the relative impacts of noncompensatory processing, threshold stopping rules, and confirmatory search in generating biased exposure. Focused studies and analyses may be able to separate these effects.

Result 4: Incidental Fixations Have Little Effect on Choice

Two kinds of incidental fixations tested have the potential to distort conjoint choices. In our studies, an alternative in the center of a choice grid and the first-accessed alternative received substantially more attention. However, that increase in fixations translated minimally into greater choices. It seems that respondents are able to discount such incidental fixations and to effectively ignore exposure to an incidental feature. The process by which that benign neglect occurs is not clear, however.

Relative freedom from distortion resulting from incidental attention is positive for conjoint choices but raises the question of why incidental fixations distort other choice tasks. There are three critical differences. First, in most conjoint exercises, the features and attributes have been introduced so that respondents already have thought about what is and is not valuable. Thus, it is easier to ignore information from an attribute that is less relevant to choice. Second, in more holistic choice tasks, such as evaluating faces or landscapes, it is often the unique aspects of those images that lead to choice. To the extent that these features are unique, mere exposure to them should have greater positive effects. Put differently, incidental exposure to features in conjoint choices may be ignored simply because these features do not provide differentially relevant information for choice. Finally, most marketplace choices are made from relatively large sets of options. As the number of options increases, it makes sense that task conditions reflected in item salience, accessibility, or simple path dependence from chance fixation would also increase their impact on choice.

These four results point to particular ways that respondents adjust their attention to cope with the demands of conjoint choices. Next, we consider extensions of our findings that delineate promising areas for further research.

First, we do not directly model noncompensatory behavior. The derived individual-level utility coefficients often are consistent with noncompensatory decision strategies. A large, positive coefficient for a particular feature is a signal that this one feature can determine choice, whereas a very large negative coefficient is consistent with the use of that feature to screen out unacceptable alternatives. However, we find minimal evidence of unbalanced search favoring the chosen object, as one would expect with a strong noncompensatory strategy. Thus, it may be the case that people are consistent in avoiding choices with strong negative alternatives but, apart from a strong focus on attractive alternatives, that strategy is not revealed in attentional behavior. However, although alternative focus captures results of noncompensatory behavior indirectly, we do not directly test such noncompensatory processes. In some decision contexts, the explicit identification of satisficing decision rules (as proposed by Stüttgen, Boatwright, and Monroe [2012]) or the computation of bounded rationality models (Reutskaja et al. 2011; Yang, Toubia, and De Jong 2015) provide important ways to understand such noncompensatory behavior.

Second, although attribute and alternative focus provide insight into the process that respondents used to make a decision, we did not detail the transition process between fixations. However, it is possible to expand the multilevel model beyond the count of within-cell fixations by exploring the transitions that precede choice. Such a model could examine the likelihood of a transition as a function of the characteristics of the current cell and the characteristics of the next cell. Such analysis could provide more detailed information on how microprocessing strategies affect choice.

Third, our analysis focuses on using only the number of fixations for each cell. We analyzed accumulated fixation durations analogously and found very similar results. Thus, expanding the analysis to include durations is unlikely to reveal novel insights. The eye-tracking data, however, also include information about pupil dilations, the number of eye blinks, and saccadic distances. The investigation of pupil dilations is expected to be of interest with changing complexities of the choice tasks because dilations appear to be a consistent index of cognitive load and arousal (Just and Carpenter 1993). Other researchers, however, have questioned whether the pupillary diameter is meaningful as a measure of attention intensity during self-paced exposure and have stressed that the primary function of the pupil is to maintain optimal vision through regulation of the amount of light, visual angle, and depth of focus (Pieters and Wedel 2007). Therefore, an open research question concerns the informative value of pupil dilations in choice contexts. Furthermore, eye blinks may index transition points within the processing flow and indicate cognitive shifts or changes in arousal. Another important task for future studies is to further investigate whether neuroscience methods (e.g., electroencephalography) can be used in combination with eye tracking to better understand attentional and decision processes (Khushaba et al. 2013). Although the analysis of these measures and methods is beyond the scope of the current article, more research is justified.

Fourth, although our data demonstrate greater respondent reliability with practice, we did not consider several opportunities that eye tracking offers for investigating unobserved error components in choice models. As suggested by Eckert, Louviere, and Islam (2012, p. 257), respondent error may be decomposed into several possible subcomponents, such as "variability in choices due to mistakes, inattention, differences in familiarity with choice options and model specifications," many of which can be resolved by models that link specific kinds of errors to processing and attentional differences.

The major surprise—and, in our view, the major contribution of this article—is the finding that the process of conjoint choices from an alternative-by-attribute grid flows from fixed respondent values rather than the unique features of each task. It is important for future studies to determine what it is about conjoint choices that lead them to be progressively more efficient, value driven, and relatively free from biases that plague other choice contexts. One factor unique to conjoint choice is the decision grid, in which a limited number of alternatives are defined by easily located attributes with comparable features. Another factor is the unpredictable assignment of features that encourages respondents to view alternatives as a combination of relatively independent features, rather than an integrated whole. Finally, the repetitive nature of the choices emphasizes the task-like nature of the conjoint exercise, which may limit emotional responses or the use of simplified cutoff strategies that could distort choices. Progress on these issues would be helpful in defining contexts in which conjoint will predict market decisions. Such issues are also relevant in defining contexts in which market decisions could be improved when framed more like conjoint tasks.

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Eye-Tracking Reveals Processes that Enable Conjoint Choices to Become Increasingly Efficient with Practice

WEB APPENDIX A – DETAILS ON THE EYE-TRACKING EQUIPMENT USED

Details on the Eye-Tracking Equipment Used

In the coffee maker study, we used the head-mounted SMI Eye-Link II System (SR Research, Inc.) with two mini-cameras that track participants' eyes. Four infrared sensors adjust the measurements to changes in participants' seating positions and therefore allow relatively free movement of participants' heads (without a chin rest). The system records eye-movements at 250 Hz on a 1280 x 1024 pixels video screen producing a deviation of measured and true gaze direction under 1.0 degree of visual angle. The software EyeDataAnalyser aligns each participant's eye movements through a standard 9-point calibration routine that requires following a dot moving around the screen.

In the vacation study, eye movements were recorded using a Tobii T120 remote eye-tracking system. This system is accurate to within .4° of visual angle and a sampling rate of 120 Hz. As in the coffee maker study, answers were given solely by using the computer mouse. The infrared sensors are built into a 17'' TFT monitor with a resolution of 1280 x 1024 pixels. Again, a standard 9-point calibration routine calibrated participants' eye movements (Tobii Software 2014).

When placing the respondent in front of the eye-tracker, we made sure that the distance indicator provided by the Tobii software displayed a value between 50 and 80 cm (ideally 60 cm) as recommended by the Tobii handbook.

Since we used binocular systems, the question remains whether to use the data from the left or the right eye. Research has shown that the accuracy is normally not identical in both eyes. We therefore used a standard test to identify the dominant eye in which respondents are first asked to point to a far object with an outstretched arm using both eyes. While still pointing, the respondent is asked to close one eye at a time. The eye that sees the finger pointing directly at the target is assumed to be dominant. In the first study, 41 of 60 respondents were right-eye dominant which is in line with previous findings which have shown that 65% of all observers are right-eye dominant (Porac and Coren 1976). We then tested whether our results were different when we used only information from the left, right or the dominant eye. The results were identical regarding the main effects of interest, i.e. alternative and attribute focus as well as the potential effects of incidental attention distortion. We therefore use the data from the right eye for both studies to simplify the analysis.

In order to define fixations, the raw eye movement data are processed further into fixations. Different algorithms have been proposed and tested to define fixations (Van der Lans, Wedel and Pieters 2011). Despite the accuracy of these algorithms, there is no objective start and end of a fixation which means that the identification process remains partly subjective (Tobii Software 2014). In study 1, we used a fixation filter provided by SR Research whereas in study 2 we used the standard Tobii fixation filter for the determination of fixations.

The areas of interest were defined as non-overlapping cells in the display matrix similar to that shown in Figure 1. All other fixations, such as on question text, descriptions of the attributes and alternatives as well as selection buttons were ignored in the analysis. The results are robust to how we define the areas-of-interest. We tested different definitions of the areas-of-interest in line with Orquin, Ashby and Clarke (2015) and the results were almost identical.

Regarding the definition of the areas of interest it has been recommended that they allow for a margin around the object which is approximately the size of the fovea (1 - 1.5°). With the stimuli we presented in our studies, we meet this criterion.

Moreover, it is important to emphasize that we used texts only to describe the features in the beach vacation study. It is therefore relatively unlikely that the features differed regarding their saliency which could have produced minor differences with respect to the number of fixations to features in the coffee maker study.

In both studies respondents reported to have normal or corrected to normal vision. However, we did not perform an eyesight test in the laboratory to check that. Moreover, in the second study we also did not use a chin rest because the Tobii eye-tracker renders the chin rest unnecessary (Duchowski 2007).

The fixation algorithms were also used to assess fixation durations, to identify saccades, blinking and pupil dilation. Similar to Glöckner et al. (2012) we here focus on the number of fixations. In line with previous studies in the field, we excluded fixations lasting less than 50ms (Fiedler and Glöckner 2012).

Due to the fact that the first fixation could influence further attention at stimulus onset, some researchers use a randomly-located fixation cross at the beginning of each trial (choice task), as used by Milosavljevic et al. (2012). We re-estimated the Poisson model results excluding the first two fixations, because we did not use a fixation cross at stimulus onset. The results of our model remain almost identical.

Details on the Experimental Processes of the Beach Vacation Study

Respondents were first asked about their purchase experience, future purchase intention as well as purchase familiarity and involvement regarding vacation packages. Subsequently, we

explained the attributes and attribute levels which were used to describe the vacation packages to respondents on several screens. Respondents then chose the best vacation package in each of 8 choice tasks. All choice tasks were randomly generated with Sawtooth Software's (2013) complete enumeration algorithm. Other questions regarding search goals (Levav, Reinholtz and Lin 2012), perceived difficulty, frustration and similarity of options as well as hold-outs and socio-demographic questions were included in the survey after the conjoint tasks.

WEB APPENDIX B – UTILITY ESTIMATES

This appendix provides details about the estimation of the multinomial choice model with random coefficients for all three studies. The utility obtained by respondent c from alternative j in choice task t, U_{cjt}, is given in Equation (A1):

$$\text{(A1) } U_{cjt} = \beta_{c0} + \sum_{k \in j} \beta_{ck} + \epsilon_{cjt}$$

where β_{c0} is an intercept reflecting the base utility of choosing one of the J objects instead of the no-choice option if available, otherwise this intercept is set to zero. β_{ck} denotes the utility contribution of feature k for consumer c when choosing an object containing that feature. The last term in this equation, ϵ_{cjt}, denotes an idiosyncratic error for object j that is assumed to be i.i.d. with an extreme value distribution having 0 mode and scale equal to 1. In addition, the utility of the no-choice option is given by $U_{c0t} = \epsilon_{c0t}$, where ϵ_{c0t} is also i.i.d. extreme value with parameters 0 and 1. To ensure identification of the model parameters we normalize the sum of all feature utilities of each attribute to zero: $\sum_{k \in a} \beta_{ck} = 0$, for all attributes a.

We then define β_c as a vector of coefficients for consumer c that includes all feature utilities except those corresponding to the last level of each attribute, which can be obtained using the identification constraint: $\sum_{k \in a} \beta_{ck} = 0$, for all attributes a. We then allow consumers to differ in their valuations of the different features of an object by letting each vector of consumer utility coefficients β_c be distributed according to a $MVN(\theta, \Lambda)$ distribution. The parameter θ determines the mean valuation across consumers while the variance covariance matrix Λ measures the degree of heterogeneity and correlation in these valuations across consumers. Estimation of model parameters is implemented using standard Bayesian MCMC methods (Rossi and Allenby 2003) in Gauss. This requires us to specify the following hyperprior distributions:

$\theta \sim MVN(0,10^2), \Lambda \sim \text{Inverse Wishart}(K+5, \Sigma)$, where K is the number of rows of Λ and Σ is equal to the following matrix for Study 1:

$$\begin{bmatrix}
2.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 1.50 & -0.50 & -0.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & -0.50 & 1.50 & -0.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & -0.50 & -0.50 & 1.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 1.33 & -0.67 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & -0.67 & 1.33 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.50 & -0.50 & -0.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & -0.50 & 1.50 & -0.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & -0.50 & -0.50 & 1.50 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.33 & -0.67 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & -0.67 & 1.33 & 0.00 & 0.00 & 0.00 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 1.50 & -0.50 & -0.50 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & -0.50 & 1.50 & -0.50 \\
0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & -0.50 & -0.50 & 1.50
\end{bmatrix}$$

Analogous hyperpriors were generated for Studies 2 and 3. As a reference, these hyperprior specifications are the same as the default options used in Sawtooth Software under this coding option.

Finally, we generate utility measures (e.g., alternative attractiveness) for each choice task that are independent of the features of the alternatives in that task. This is accomplished by estimating the utility of each feature using the data from all other choice tasks (e.g., if respondents complete T choice tasks, when estimating the utility function for choice task 3, we will use choices from choice tasks 1,2,4,5,..,T). Consequently, if a respondent completes T choice tasks, we perform T utility estimations, where in each of these T estimations we leave out a different choice task.

WEB APPENDIX C – A DETAILED ANALYSIS OF THE CENTRAL FIXATION BIAS EFFECT

Chandon et al. (2009) suggest that respondents who want to evaluate the right alternative are likely to fixate on the middle alternative located in the center while on their way to right (and vice versa). If so, "these stepping-stone fixations may mostly serve the 'where' (orientation) component of attention rather than the 'what' (identification) component" (p. 16). In their study the authors find that the 25% of fixations away from the center were significantly longer than the 25% of fixations being nearer to the center. In study 1, we find that fixations to the right alternative (M(right) = .240 seconds, SE = .133) are on average significantly longer than fixations to the left (M(left) = .231 seconds, SE = .131, t(right, left) = 3.249, $p < .001$) and to the middle alternative (M(middle) = .230 seconds, SE = .136, t(right, middle)=3.758, $p < .001$). The left and middle alternatives are not significantly different with respect to average fixation durations (t(left, middle) = .511, $p = .61$).

These results suggest that the extra attention to the middle alternative might disappear if we exclude short fixations from further consideration. We recalculated the percentages of attention to the left, middle and right alternative and excluded relatively short fixations (< .150 seconds). Our results remain qualitatively unchanged. We also redid our analysis excluding the initial two fixations and the results were also qualitatively unchanged. The latter results show that the starting position for the eye-movement sequence is relatively unimportant for the effects demonstrated in this paper because the attentional sequences are relatively long for multi-attribute decisions (about 30 fixations in each choice task for the coffee maker study and even longer for the other two studies). Moreover, we also performed a simulation in which we deleted fixations in 4ms intervals (note that we have very precise data regarding fixations durations

because we used eye-tracking equipment with 250Hz in the coffee maker study). As Figure A1 shows, the middle alternative constantly received a significantly higher amount of attention independent of how many fixations we deleted based on fixation durations.

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TABLES IN THE WEB APPENDICES

Table A1: Fixations and Choices by Horizontal Position (Beach Vacation Study)

	Left Alternative	**Left from the Center Alternative**	**Center Alternative**	**Right from the Center Alternative**	**Right Alternative**
Percent of fixations	21.0%	24.1%	22.1%	18.9%	13.9%
Standard error	(.019)	(.009)	(.015)	(.019)	(.017)
Percent chosen	20.1%	18.4%	20.7%	23.4%	17.4%
Standard error	(.074)	(.058)	(.108)	(.093)	(.056)

Table A2: Fixations and Choices by Horizontal Position (Laptop Study)

	Left Alternative	**Left from the Center Alternative**	**Right from the Center Alternative**	**Right Alternative**
Percent of fixations	22.6%	30.2%	27.7%	19.5%
Standard error	(.078)	(.067)	(.069)	(.063)
Percent chosen	20.9%	22.3%	30.4%	26.4%
Standard error	(.228)	(.200)	(.254)	(.217)

Table A3: Multilevel Analysis of Factors Influencing Fixations in Three Studies (Beta Coefficients and Cell-level Model; * p < .05, ** p < .01, *** p < .001)

Study	Coffee maker		Beach Vacation		Laptop	
Model Term	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Fixed effects coefficients						
Alternative attractiveness	.343***	.010	.287***	.009	.401***	.005
Alternative attractiveness * Task progression	.119***	.013	.329***	.017	.250***	.009
Alternative attractiveness * Task experience	.116***	.018	.084***	.018	.094***	.010
Attribute importance	.226***	.006	.152***	.007	.316***	.003
Attribute importance * Task progression	.146***	.011	-.038***	.015	-.311***	.007
Attribute importance * Task experience	.060***	.011	.057***	.015	.055***	.007
Feature utility	-.028***	.006	-.012	.008	-.058***	.004
Feature utility * Task progression	.000	.011	-.043***	.015	-.036***	.007
Feature utility * Task experience	-.024**	.012	-.036**	.016	-.028***	.007
Task progression	-.054***	.012	-.068***	.016	.048***	.008
Task experience	-.270***	.034	-.295***	.053	-.266***	.024
Horizontal centrality	.182***	.012	.073***	.008	.172***	.004

Alternative first fixated	.127***	.013	.228***	.018	.155***	.008
Task difficulty	.059***	.018	.022	.028	.048***	.012
Random effects variances						
Task nested within respondents	.169***	.011	.186***	.018	.175***	.008
Respondents	.157***	.032	.157***	.043	.137***	.025
Model fit						
Log likelihood	-44805.610		-33755.473		-122103.944	
Number of observations	25920		18240		67200	

FIGURES IN THE WEB APPENDICES

Figure A1: Average Fixation Durations for the Left, Middle and Right Alternative When Excluding Fixations of Varying Intervals