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

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ABSTRACT

Choice-based conjoint is a popular way to characterize consumers’ choices in the marketplace. It is very useful in defining consumer segments and assessing the impact of product features on choice share. Across three studies, eye-tracking reveals decision processes in conjoint choices that take less time and are more accurate with practice. We observe two simplification processes that are associated with greater speed and reliability. Alternative focus gradually shifts attention towards options that represent promising choices, while at the same time attribute focus directs attention to important attributes that are most likely to alter or confirm a decision. Both alternative and attribute focus increase in intensity with practice across choices. In terms of biases, we detect a small but consistent focus on positive aspects of the item chosen and negative aspects of the items not chosen. We also show that incidental exposures arising from the alternative first examined or from a central horizontal location greatly increase attention but have a much more modest and often insignificant impact on conjoint choices. Overall, conjoint choice is revealed to be a process that is largely formed by goal-driven values that respondents bring to the task, one that is relatively free of distorting effects from task layout or random exposures.

Keywords: Eye-tracking, conjoint, choice models, attention, preference, incidental exposure, goal-driven processes, Poisson model
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Observation of eye movements has provided significant insights into the processes underlying consumer product choice. In this paper, eye-tracking enables us to better understand the processes that respondents use when completing a conjoint exercise that involves repeatedly choosing among alternatives where alternatives 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 towards attractive alternatives and important attributes. Alternative focus consistently increases as the decision approaches. Further, with experience across tasks respondents increase their efficiency increasing their attention on important attributes and attractive alternatives. These processes are consistent with a goal-driven causality mechanism where attention depends on stable values each respondent brings to the task.

Eye-tracking enables an assessment of whether task layout or random exposures distort attention and choice. We find that attention to features within an alternative is affected by whether that alternative is chosen or not, with relatively more attention to positive than to negative features of chosen objects. However, we find little evidence of stimulus-driven attention influencing choice in repeated conjoint tasks. The empirical results show that both the alternative examined first and the centrally positioned alternative receive a higher amount of attention, but this additional attention does not reliably influence the probability of choosing an alternative. The major lesson is that the main drivers of both attention and choice are the stable utility values that people bring to the task.

The two first sections of the paper review research on general choice processes that characterize when attention arises from respondent goal-driven values and when it arises from
the stimulus-driven properties of the task. The following section explores the ways conjoint choice processes can be expected to be different from one-time, unstructured decisions, and ends with a series of research questions the studies are designed to answer. We then present results from three conjoint studies, arising from different product categories, choice designs and choice tasks. The analysis begins with relatively simple analyses clarifying ways in which conjoint choices can be distorted by common contextual biases, and evidence that focus on attractive alternatives and important attributes enables more effective conjoint choices. These initial analyses are then complemented with a Poisson model of the count of fixations on each feature that simultaneously accounts for different aspects that alter attention. Those analyses more clearly reveal the processes by which value-based attention develops within and across choice tasks.

Even though this article reveals a process of conjoint choices that is quick, efficient and less susceptible to common contextual biases, there are two related issues that go beyond its scope. First in terms of process, we characterize attentional processes 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 reflecting 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, while 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 why conjoint choice exercises are successful in identifying stable values that underlie tradeoffs.
GOAL- AND STIMULUS-DRIVEN ATTENTION

Two mechanisms jointly explain attentional processes in choice tasks: goal-driven attention 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 saliency, location, or forced exposure. We propose that distortion of choices is possible under both mechanisms: goal-driven attention could lead to heuristics and shortcuts arising from trying to quickly identify a satisfying decision alternative, while 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). Below we review research that documents increasing attention to promising alternatives and to important attributes is associated with a high utility choice. Then we will show how the goal of increasing certainty and decreasing effort may lead to motivated attention and a shift in values that increase the likelihood of choosing the current alternative.

Alternative Focus. Studies consistently show that the finally chosen alternative receives substantially more attention than non-chosen ones (Pieters and Warlop 1999; Shimojo et al. 2003). This result has been replicated recently 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 tight correspondence between attention and search by demonstrating how the current evaluation of an
alternative can influence subsequent search for information. Once an alternative becomes the preliminary leader then more attention is focused on it. Information search and comparison processes are then more favorably disposed towards the features of that leading alternative, producing more attention directed towards the chosen alternative that become stronger as the decision approaches.

We will show that high-valued alternatives in conjoint choice tasks receive increased attention. We add to this research by assessing the extent to which the focus on attractive alternatives increases as the task progresses 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, Johnson et al. (1997) show that respondents process information more attribute-wise for the attribute “brand.” The authors also observe that respondents look more at that attribute in the first half, but not in the second half of the decision process. Harte, Koele and van Engelenburg (1996) compare attribute importances derived from an estimation of multi-attribute utilities with attribute weights from information-display boards capturing the amount of information searched. They observe an average correlation of about 0.9 between both sets of values, demonstrating that important attributes receive more attention.

In line with Cattin and Wittink (1982), we define relative attribute importance as the range in an individual’s utility for an attribute divided by the sum of ranges across all attributes. Using that definition we test whether respondents making conjoint choices differentially focus attention on important attributes. Moreover, we assess whether the attribute focus effect increases within as well as across choice tasks.
Greater Attention to Positive or Negative Features Depending on Choice. If a goal is to quickly choose an alternative then that desire should result in greater fixations on positive features for the chosen alternative. There are three processes that could lead to such a result. Imbalance could come from non-compensatory processing, from satisficing heuristics that stop search when an alternative passes an acceptability threshold, and from actively searching for information that confirms a current favorite. These processes are briefly discussed below.

Non-compensatory processing has been shown to characterize choices (Gilbride and Allenby 2004). It can take two primary forms in conjoint. Either one can screen out alternatives that have an undesired feature or only consider those that have a desired feature. These strategies imply that rejected alternatives are more likely screened out from negative information while 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 once an alternative is sufficiently attractive, 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 one 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 known to be positive can lead to faster and more confident choice. The rich literature on search to justify choice (Brownstein
2003) shows that 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 non-compensatory processes to manifest early in the choice process, since the goal of cutoffs is to simplify later choice processes. By contrast, since 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 towards 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 coming from the form and location of stimuli in the task.

*Manipulated Attention.* Several empirical studies have manipulated attention and found that it alters choice. Armel, Beaumel, and Rangel (2008) alter the duration of attention to pairs of food choices by presenting one decision alternative for 300 and the other for 900 milliseconds. They show that greater manipulated attention increases the probability of choosing the alternative. The authors see this result to be consistent with a mere exposure effect, where 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 which respondents spend on 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 alternative 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 the ability of consumers 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 one another to form a cascade that reaches a peak just prior to the decision. However, this explanation of the gaze cascade effect has been questioned in recent studies (see, Bird, Lauwereyns and Crawford 2012; Glaholt and Reingold 2009). Our work here also questions the stimulus-driven link in a gaze cascade in conjoint choice to the extent that we find little evidence that the two stimulus-driven attentional factors described below 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 investigated the effect. They replicate respondents’ tendency to look at a central alternative initially and additionally demonstrate focus on the central alternative just prior to the decision. They called 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, then attention to
the central position may be seen as stimulus-driven, arising from ease of accessibility, or it could be 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 each other. They show that respondent’s attention focuses on the central alternative among art works, but that difference only alters choice where the three alternatives are virtual copies of one another.

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

*Alternative First Fixated.* 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 more likely to choose that first item. In a recent study (Fisher and Rangel 2014), respondents had to decide whether they would eat a bundle including 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 bundle. These results suggest that the feature first fixated on might lead to more choices.
Our studies of conjoint choices test whether the first alternative fixated on gets more attention and whether that attention alters choice probabilities. Before that we explore reasons why the results for conjoint choices may diverge from the results reviewed above.

*How Conjoint Choices are Different*

Many of the eye movement studies reviewed above 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. The conjoint choices further differ in having features that are generally arrayed in a matrix where attributes are placed in consistent rows. The lattice structure enables respondents to quickly find important attributes to hone in on 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, or 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 interactions. If so, then in a conjoint choice the value of an 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 for the individual. It is facilitated in conjoint choice tasks where the attributes are in defined horizontal locations. Therefore, it is relatively easy to learn the locations of the most important attributes and to focus on those attributes that have the most impact on preferences. If it helps make decisions, we can expect attribute focus 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 individual’s utility for the option?*
2. *To what extent does the focus on each attribute reflect the individual’s importance of that attribute?*
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 an individual’s utilities determine the attentional processes in conjoint choices. A unique feature of conjoint exercises is the 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 relation between fixations and choice. To circumvent this problem, for each choice task we will 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 will use choices from choice tasks 1,2,4,5,...,T). This ensures that the utility measures (i.e., alternative attractiveness, attribute importance and feature utility) for a given choice task are independent of the identity of the chosen alternative in that choice task. Consequently, the use of these hold-out estimates provide assessments of the impact of individual utilities on alternative and attribute focus that are statistically unrelated to the specific alternatives chosen in each task. Further, the analysis can test for distorted search for information depending on choice and assess whether incidental fixations alter choices.

The next section explores 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. We also show that contextual biases commonly found in other settings are much less salient in conjoint choices. Then follows a section that formulates a comprehensive attentional model built around the number of times a respondent accesses each piece of information in the choice task. This analysis enables an estimation of the extent that 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 different
conjoint studies. Finally, we summarize the theoretical implications of our findings for choice-based conjoint.

We present analyses from three quite different conjoint studies, involving choices among coffee makers, beach vacations and laptops. We will provide an elaborate description of the analysis of the coffee maker study, and will spend less time on the other studies as those details are available elsewhere.

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 excluding cases with incomplete data due to calibration or data recording problems and two participants who chose none of the purchase options in all choice tasks.

The analysis focuses on 12 conjoint choice tasks similar to that shown in Figure 1 between three single-cup coffee brewers and a no-choice option. Study participants learned about the attributes and then made four warm-up practice choices. Additionally, two other fixed tasks were included between the random tasks 6 and 7. While these six additional tasks are not included in our analysis, the results differ little if they are.

The attribute levels of the choice illustrated in Figure 2 come from a total of 20 different features. Sawtooth Software’s (2013) system generated randomized choice tasks. Within each respondent the choice design is approximately orthogonal across attributes and balanced with respect to the levels of the features.
A binocular video-based and head-mounted eye-tracker recorded eye movements. The SMI Eye-Link II System (SR Research, Inc.) includes two mini-cameras which track participants’ eyes. Detail on the system is provided in web appendix 1.

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 the responses where subjects chose one of the alternatives shown, but not the no-choice option. Finally, we use the number of fixations on the feature as our measure of attention to a feature, although we get very similar results if we instead use 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. Then, we will 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.

The analysis begins by estimating feature utilities for each respondent with a Bayesian random-coefficients multinomial logit choice model with normally distributed heterogeneity in consumer coefficients estimated using Markov chain Monte Carlo simulation. Appendix 2 provides detail on the hierarchical specification. Figure 2 displays the means and standard deviations of each feature across respondents. On average the price of the unit and the price per cup are the most important attributes, but there are substantial differences in attribute values across respondents.

Figure 3 plots average accuracy and number of fixations across the tasks. The hitrate is estimated by holding out each of the 12 tasks and predicting its choice from the 11 remaining
tasks. That process generates an average hitrate of around 68% correct predictions across the three purchase and the no-purchase options. More importantly, the hitrate improves over time by around 12 percentage points (B=1.07, t=3.099, p=0.011). Concurrently, the number of fixations decreases from 50 fixations to about 32 fixations (B=-1.651, t=6.271, p <0.01). A similar graph replacing fixations with seconds shows a drop 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 a number of 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

Figure 4 investigates alternative focus by considering the probability of fixating on an alternative as a function of its estimated utility. Combining 60 respondents by 12 tasks and 3 alternatives and taking out the 15% who chose none generates 1833 observations. The graphs show that alternatives with higher total utilities generate more attention while 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=0.012, is significantly smaller than for the last six tasks (B_{diff}=0.016, t=3.321, p<0.01) and they are both significantly different from zero (p<0.01).

The focus on attractive alternatives is not surprising but follows research discussed earlier suggesting that the chosen alternative receives more attention. Further, the fact 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 60 respondents for 6 attributes generates 360 observations.

Figure 5 shows that attributes with greater respondent importance generate greater attention overall and that attribute focus increases with practice, but this increase is not significant (t=1.082, p=0.28).

_Evidence for Biased Attention Depending on Choice_

Because people focus attention on attractive alternatives, it makes sense that features with high utility and connected with the chosen alternative get more attention. However, a more interesting question is whether there is biased towards high-utility features of chosen alternatives. As discussed earlier, finding such a bias could be evidence of a screening rule that shifts focus away on the basis of an undesired feature, from a threshold choice model that makes the choice of an alternative more likely following focus on desired features, or from motivated search that drives attention towards evidence justifying the current option.

Figure 6 graphs the percentage of attention to a feature within an alternative against the standardized relative utility within an alternative. For chosen alternatives there is a greater tendency to focus on more positive (B=0.011, t=3.256, p<0.01) but the reverse occurs for rejected alternatives (B=-0.005, t=-1.595, p=0.111). Thus a one standard deviation shift in the relative utility increases attention across the six features of an alternative feature by \(0.11/0.166=6.7\%\) for a chosen alternative but decreases it by \(0.0054/0.166=3.2\%\) for rejected ones.
Given that there are a number of distinct processes that generate greater attention to positive features of chosen alternatives, what is surprising is the relative weakness of the effect, particularly when compared with the strong impact of attractive attributes and important attributes. We will 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 simplify the choice process that can increase the efficiency and accuracy of choice. In this section we examine the impact of attention stemming from the random allocation of features to alternatives or to their horizontal location among the three choice options. We consider two forms of stimulus-driven attention driven by the centrality of the choice or by the identity of the first alternative viewed.

Consider first centrality. With three alternatives, it is reasonable that the one in the center receives more fixations, simply because it is 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 is shifted toward the right. A simple linear trend is significant and negative for the left alternative ($B_l = -0.45, p<0.01$), significant and positive for the right alternative ($B_r=0.26, p<0.01$) and significant and positive for the middle alternative ($B_m=0.34, p<0.01$). In all, the middle alternative, due to its location, gets around 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 a couple of different possible explanations, ranging from the center being a convenient location from which
to start oculomotor exploration to a tendency to re-center the eye in its orbit (Tatler 2007). The central fixation bias effect for our data is more closely investigated in Table 1 and in web appendix 3.

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, then that should produce greater choice of the middle alternative. Middle alternatives receive 34% of choices versus the corresponding 33% for non-central alternatives. We test the significance of this difference with a simple logit model predicting choice as a function of whether the alternative is in the middle of the screen. The 1.0 percentage point increase in attention from centrality generates a non-significant coefficient for centrality (B=0.0159; t=0.37; p=0.71).

Thus, in this study we find no evidence of centrality affecting choices. This result contrasts with the findings of Atalay, Budur and Rasolofoarison (2012), where in a non-conjoint context the middle alternative generated both more fixations 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 alternative examined first. Since 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 see if that unplanned exposure alters choice probabilities. The alternative first examined averages 15.14 fixations compared with 13.13 fixations for the other alternatives. This 15% difference is strongly significant (t=3.881; p<0.01). However, the first exposure generates
36.5% choices compared with 31.75% for the other two alternatives. This 14% difference is not significant (B=0.139; t=1.130 p=0.257) when tested using a logit choice model.

Summary

These results are important because they identify simple processes that enable conjoint respondents efficiently perform a difficult task. 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 slightly more on positive features of chosen and negative features of rejected alternatives. Finally, there is no evidence that the 21% greater number of fixations on the middle alternative alter choice or evidence that the 15% greater number of 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 of number fixations on each cell 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. Further, it controls for other factors that influence attention such as the effect of attribute position, the identity of first examined alternative and the difficulty of the choice.
A GENERAL MODEL OF CELL ATTENTION

The preceding analysis has examined attention to alternatives, attributes and features individually, and revealed reasonable attentional patterns of search and decision making. An integrated model of attention in each task derives from the count of fixations each respondent makes on the 18 cells in the three-by-six attribute choice grid shown in Figure 1. A Poisson count model with a log link function is appropriate as it assumes that the expected frequency of attending 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 those attended in the first or second group of six tasks, the analysis can assess the degree to which fixations shift with practice. Finally, it allows 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, \( \sum P_j \left( \ln P_j \right) \) of the individual’s predicted choice probabilities \( (P_j) \).

Since each cell is an observation, there are 25,920 observations (60 respondents, 12 tasks per respondent, 18 cells per task, and two halves for each task). Obviously these are not independent, so the model accounts with random coefficients for respondents at the highest level and then tasks at the second level.

Formally, we assume a multilevel Poisson model of cell fixations:

\[ y_{ijkth} \sim \text{Poisson}(\lambda_{ijkth}) \]

with:
\[
\ln \lambda_{ijkth} = \alpha_i + \beta_{t(i)} + \gamma_h + \delta X_{ijkth},
\]

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

- \(\alpha_i\): 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;
- \(\gamma_h\): task half fixed effect;
- \(X_{ijkth}\): a vector of characteristics of cell \((j,k)\) for participant \(i\) in half \(h\) belonging to choice task \(t\);
- \(\delta\): the corresponding vector of coefficients for \(X_{ijkth}\).

The model parameters are then estimated via maximum likelihood (we note that Bayesian estimation yields almost identical results).

To facilitate interpretation, we standardize the four continuous measures of alternative attractiveness, attribute importance, feature utility and difficulty. We also zero-center the four categorical variables of task progression, task experience, horizontal centrality, and the alternative first fixated. Table 4 provides multilevel results across the three studies. We here focus on its first column that provides percent change results and \(t\)-test for the coffee maker study. We will later examine the results for the other two studies. The first column of Table 4 shows the percentage change in fixating on a particular cell and the appropriate \(t\)-test. The latter
were derived by exponentiation of the raw Poisson coefficients that are provided in web appendix 3.

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. Looking at the second row, 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 $1.409 \times e^{-0.119/2}-1 = 32.8\%$ increase in fixations with an increase of one standardized unit of alternative utility. By contrast in the second half there is a corresponding 49.5% (i.e., $1.409 \times e^{0.119/2}-1$) increase. These results provide a multivariate replication of the bivariate analyses shown earlier 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 attention moves to trading off differences among important attributes rather than examining value for less important ones.

Feature utility has reliable but modest effects. The significant negative effects of feature utility and their expansion across tasks were not hypothesized but are potentially 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 briefly comment on the control variables shown in Table 4. As noted earlier, both centrality and the first alternative fixated generate significantly greater attention. Further, showing that fixations are 24% less likely in the last six tasks corresponds roughly with the drop in decision time with practice shown in Figure 2. The greater number of fixations for choice tasks with higher entropy means that respondents appropriately spend more time and attention on difficult choices where utilities are less far apart. That result is consistent with Fisher and Rangel (2014) showing 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 are more likely to focus on attractive alternatives and important attributes. However, as choice progresses both alternative and attribute focus increase strongly. That makes sense if in the first half of each task respondents are broadly scanning the matrix. However, as the decision approaches attention gravitates to the important aspects of likely choices.

The lack of measurable contextual biases in this conjoint study contrast 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 if the results are study specific.

TWO CONCEPTUAL REPLICAATIONS

The replications come from eye tracking of conjoint studies that are deliberately different from the coffee maker study. The first replication is a conjoint study of beach vacations detailed
in (Left out to preserve anonymity). The second replication is a conjoint study of laptops from Yang, Toubia, and de Jong (2015). We thank the authors for making these data available.

Table 2 provides a summary of the important differences across the studies. They differ with respect to the product category, since coffee makers and laptops are relatively utilitarian durables, whereas the beach vacations reflect a short term hedonic experience. The number of alternatives per choice shifts from three to four and five, and the number of distinct features varies from 18 to 24. The designs also differ. Both the coffee maker and the beach vacation use Sawtooth Software’s randomized design on 12 and 8 tasks respectively. The laptop study employed 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. Table 3 gives the measures of efficiency and bias for the three studies. In both 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 hold-out choices, increases by around 15% across the three studies. However, that increase is not statistically significant for the beach vacation study.

Incidental fixations from either the first focused alternative or centrality demonstrate strongly consistent shifts in attention that varies from 16% to 38%. Except for the centrality in the laptop study, the shift in choice is non-significant. Thus across studies we find that the first fixated alternative and centrality 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. Detailed centrality statistics are given in Tables A1 and A2 in the web appendix.

Table 3 also examines whether there is a bias towards 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 to focus on the first fixated or central alternatives.

Table 4 summarizes the percent changes in attention from the multi-level analysis of attention across studies. Details and the raw statistics for those analyses are given in Table A3 in the web appendix. 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% to 49%. Further, in all cases that shift increases by 13% to 39% within task and around 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 around 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% moving to the second half of fixations within a task, whereas for the beach vacation study attention to important attributes drops by 4%, while in the laptop study the drop is 27%. That negative shift in the second half implies that respondents examine less important attributes just close to choice. The substantial shift to less important attributes is reasonable in the case of the
incentive compatible laptop study if before making a final decision respondents are 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 they are more prevalent for first fixated and centrally located alternatives. Greater task difficulty measured by the entropy of the choice task increases the number of fixations as would be expected. Further 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

A number of robustness checks confirm the stability of our results across all three studies. These include using a Negative Binomial (NB) model instead of the Poisson model (i.e., allowing for over-dispersion of the fixation data) and also 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 upon 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 task progression and task experience also replicate, although a few interactions became marginally significant. Finally, a linear specification yields an inferior fit compared to the Poisson and NB models, where fit is assessed based on the Akaike and Bayesian information criteria. This suggests that the impacts of the cell characteristics such as 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 further that there is very little evidence for stimulus-driven attention or susceptibility to incidental fixations altering choice.

It is important to note the role of repetition in conjoint choices in being able to derive these results, as they enable the independent estimation of alternative attractiveness, attribute importance and feature utility for each choice. While there are programming and computational costs in estimating different preference structures for each task as a hold-out, these estimates are important for our results. In particular, since the models estimate around 20 parameters from 7, 11, to 19 choices, there is substantial over-fitting if hold-out predictions are not used. In particular, instead of correctly predicting around 60% of the hold-out choices, the Bayesian model that pools all choice tasks has an internal hit rate of nearly 85%, indicating that the model successfully adapted to task differences in each choice set.

The three studies point to a conjoint choice process in which respondents learn to be more efficient and effective in their choices by focusing on attractive alternatives and on 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. Four major results are summarized and commented upon below.

**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 grows within tasks and across tasks with practice. The growth within tasks was expected and 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 at 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 previous findings, and suggest a reason why 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 more important attributes. Focus on important attributes increases with practice in all cases, consistent with gradual increase in the ability to identify and find important information relevant to the choice.

Attribute focus increases within a task for the coffee maker study, it slightly but significantly decreases for the beach vacation study, and decreases strongly so for laptop computers. 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 is clear from Figure 9, three attributes, processor
speed, price and hard drive dominate. These three attributes may be initially used to identify
important candidates while 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: Feature utility has minor impact on attention after accounting for alternative
attractiveness and attribute importance. 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 as
it is reasonable to expect that features about which respondents care deeply will 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 focus attention. That
ease of processing account agrees with the finding that with experience both attribute importance
and alternative attractiveness increase, while 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. Additionally, 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. Further, choices in the marketplace abound with surprising,
salient and important features, as we see where 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 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, that analysis indicates that negative features get more attention, and that negativity effect is significantly greater for rejected over chosen alternatives. That result begs the question of the relative impact of non-compensatory processing, threshold stopping rules, and confirmatory search 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 alternative accessed get substantially more attention. However, that increase in fixations translates minimally into greater choices. It appears that respondents are able to discount such incidental fixations and are able to effectively ignore an incidental feature. The process by which that benign neglect occurs is not clear, however.

Relative freedom from distortion resulting from incidental attention is a good sign 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 have been introduced so that respondents already have thought about what is valuable and what is not. Thus, being exposed to a feature that is less relevant to choice can be more easily ignored. 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 should have greater positive effects. Put differently, incidental exposure to features in conjoint choices may be ignored simply because they do not provide differentially relevant information for choice. Finally, most choices are 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 will 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. Below we consider extensions of our findings that delineate promising areas for future research.

First, we do not directly model non-compensatory behavior. The derived individual level utility coefficients often are consistent with non-compensatory decision strategies. A large positive coefficient for a feature is a signal that one feature can determine choice, while a very large negative coefficient is consistent with using that feature to screen out unacceptable alternatives. However, it should be noted that we find minimal evidence of unbalanced search favoring the chosen object, as one would expect with a strong non-compensatory 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. Put differently, while alternative focus captures results of non-compensatory behavior indirectly, we do not directly test such non-compensatory 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 non-compensatory behavior.
Second, while attribute and alternative focus provide insight into the process used, we have not detailed the transition process that led to the pattern of aggregate fixations. However, it is possible to expand the multilevel model beyond the count of fixations within cell by exploring the transitions that precede choice. Such a model could examine the likelihood of 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 micro-processing strategies affect choice.

Third, our analysis focuses on only using the number of fixations for features, attributes and alternatives. We have 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 includes 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, as 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. Further, eye blinks may index transition points within the processing flow and indicate cognitive shifts or changes in arousal. Another important task for future research is to further investigate whether neuroscience methods, like electroencephalogram (EEG), can be used in combination with eye tracking to better understand
attentional and decision processes (Khushaba et al. 2013). While the analysis of these measures and methods is beyond the scope of the current paper, more research is justified.

Fourth, while our data demonstrates greater respondent reliability with practice, we have not considered a number of opportunities eye tracking offers for investigating yet unobserved error components in choice models. As suggested by Eckert, Louviere and Islam (2012), 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” (p. 257) 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 paper, is in showing that the process of conjoint choices from an alternative-by-attribute grid flows from relatively fixed respondent values rather than the unique features of each task. It will be important for future research 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, where 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 that may limit emotional responses or the use of simplified cutoff strategies that could distort choices. Progress on these issues will be helpful in defining contexts in which conjoint will predict market decisions. It also is relevant in defining contexts in which market decisions can be improved when framed more like conjoint tasks.
REFERENCES


Sawtooth Software Inc. (2013), CBC/HB v5: Software for Hierarchical Bayes Estimation for CBC Data, Orem, UT.


Figures and Tables

Figure 1: Choice Task for Coffee Maker Study

If you were in the market to buy a new single-cup coffee brewer and these were your only options, which would you choose?

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand</td>
<td>Krups</td>
<td>Philips</td>
<td>Severin</td>
<td></td>
</tr>
<tr>
<td>Material</td>
<td>Plastic</td>
<td>Brushed aluminium</td>
<td>Stainless steel</td>
<td>None: I wouldn't choose any of these.</td>
</tr>
<tr>
<td>System</td>
<td>Pad</td>
<td>Capsule</td>
<td>Pad</td>
<td></td>
</tr>
<tr>
<td>Design</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price of a cup</td>
<td>32 €/cup</td>
<td>22 €/cup</td>
<td>12 €/cup</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>189.99</td>
<td>129.99</td>
<td>159.99</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2: Feature Utilities with Standard Deviations across Respondents for the Coffee Maker Study

![Figure 2: Feature Utilities with Standard Deviations across Respondents for the Coffee Maker Study](image)

Figure 3: Hitrate and Decision Time across Tasks for the Coffee Maker Study

![Figure 3: Hitrate and Decision Time across Tasks for the Coffee Maker Study](image)
Figure 4: Attention to an Alternative Increases with the Attractiveness of the Alternative and that Relationship Increases with Practice

**Percent of attention to an alternative**

- **Task 1-6**
  - $y = 0.0122x + 0.3343$
  - $R^2 = 0.2142$

- **Task 7-12**
  - $y = 0.0158x + 0.3323$
  - $R^2 = 0.2549$
Figure 5: Attention to Attributes Increases for Important Attributes But Is Not Significantly Higher with Practice

**Percent of attention to an attribute**

Task 1-6  
\[
y = 0.2681x + 0.122  
R^2 = 0.1332
\]

Task 7-12  
\[
y = 0.3811x + 0.1031  
R^2 = 0.2113
\]

Figure 6: Attention to Features Increases with Greater Utility for Chosen Alternatives But Decrease for Rejected Alternatives

**Percent of attention to a feature**

**Not chosen**  
\[
y = -0.0045x + 0.1597  
R^2 = 0.0021
\]

**Chosen**  
\[
y = 0.0108x + 0.1604  
R^2 = 0.01
\]
Figure 7: Shift in Alternative Fixations as Decision Approaches

Percent attention to alternatives

Time until decision (seconds)

- Middle alternative: $R^2 = 0.0713$
- Left alternative: $R^2 = 0.1718$
- Right alternative: $R^2 = 0.0811$

Equal attention
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
Tables

Table 1: Fixations and Choices by Horizontal Position of Coffee Makers

<table>
<thead>
<tr>
<th></th>
<th>Left Alternative</th>
<th>Middle Alternative</th>
<th>Right Alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of fixations</td>
<td>33.1%</td>
<td>37.5%</td>
<td>29.4%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(.022)</td>
<td>(.020)</td>
<td>(.026)</td>
</tr>
<tr>
<td>Percent chosen</td>
<td>32.6%</td>
<td>34.0%</td>
<td>33.4%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(.055)</td>
<td>(.066)</td>
<td>(.083)</td>
</tr>
</tbody>
</table>

Table 2: Differences between the three Eye-tracking Conjoint Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Coffee maker</th>
<th>Beach Vacation</th>
<th>Laptop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student respondents</td>
<td>60 European</td>
<td>35 Australian</td>
<td>70 European</td>
</tr>
<tr>
<td>Number of alternatives</td>
<td>3: None</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Number of distinct features</td>
<td>20</td>
<td>18</td>
<td>24</td>
</tr>
<tr>
<td>Number of choice tasks</td>
<td>12</td>
<td>8</td>
<td>20</td>
</tr>
<tr>
<td>Design within choice tasks</td>
<td>Randomized</td>
<td>Randomized</td>
<td>Fixed across subjects</td>
</tr>
<tr>
<td>Design within subjects</td>
<td>Orthogonal and level balanced</td>
<td>Orthogonal and level balanced</td>
<td>Totally random</td>
</tr>
<tr>
<td>Incentive compatible</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Data conducted by</td>
<td>Authors of this article</td>
<td>Authors of this article</td>
<td>Yang et al. (2015)</td>
</tr>
</tbody>
</table>
### Table 3: Measures of Efficiency and Attentional Biases across the Three Studies

<table>
<thead>
<tr>
<th>Study</th>
<th>Coffee maker</th>
<th>Beach Vacation</th>
<th>Laptop</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% change</td>
<td>Significance</td>
<td>% change</td>
<td>Significance</td>
<td>% change</td>
</tr>
<tr>
<td><strong>Efficiency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drop in number of fixations with practice</td>
<td>-36%</td>
<td>t=6.271; p&lt;0.01; n=720</td>
<td>-48%</td>
<td>t=5.745; p&lt;0.01; n=304</td>
<td>-25%</td>
</tr>
<tr>
<td>Gain in accuracy with practice</td>
<td>+19%</td>
<td>t=3.099; p=0.011; n=611</td>
<td>+18%</td>
<td>t=1.383; p=0.168; n=304</td>
<td>+14%</td>
</tr>
<tr>
<td><strong>Incidental fixations: Attentional distortion to first alternative accessed</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focus on alternative first fixated</td>
<td>+15%</td>
<td>t=3.881; p&lt;0.01; n=1833</td>
<td>+29%</td>
<td>t=4.604; p&lt;0.01; n=1520</td>
<td>+16%</td>
</tr>
<tr>
<td>Greater choice for alternative first fixated</td>
<td>+14%</td>
<td>t=1.130; p=0.257; n=1833</td>
<td>-4%</td>
<td>t=0.140; p=0.892; n=1520</td>
<td>-11%</td>
</tr>
<tr>
<td><strong>Incidental fixations: Attentional distortion to alternatives in the center of the choice set</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focus on central alternatives</td>
<td>+21%</td>
<td>t=5.302; p&lt;0.01; n=1833</td>
<td>+24%</td>
<td>t=4.370; p&lt;0.01; n=1520</td>
<td>+38%</td>
</tr>
<tr>
<td>Greater choice for central alternative</td>
<td>+3%</td>
<td>t=0.670; p=0.506; n=1833</td>
<td>+11%</td>
<td>t=0.580; p=0.563; n=1520</td>
<td>+14.3%</td>
</tr>
<tr>
<td><strong>Change in attention from an increase in standardized feature utility depending on</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chosen alternative</td>
<td>7%</td>
<td>t=3.256; p&lt;0.01; n=1200</td>
<td>4%</td>
<td>t=2.119; p=0.034; n=684</td>
<td>7%</td>
</tr>
<tr>
<td>Rejected alternative</td>
<td>-3%</td>
<td>t=1.595; p=0.111; n=1200</td>
<td>-6%</td>
<td>t=2.388; p=0.017; n=684</td>
<td>-16%</td>
</tr>
</tbody>
</table>
Table 4: Multilevel Analysis of Factors Influencing Fixations in Three Studies

<table>
<thead>
<tr>
<th>Study Term</th>
<th>Coffee maker</th>
<th>Beach Vacation</th>
<th>Laptop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Term</td>
<td>% change</td>
<td>Significance</td>
<td>% change</td>
</tr>
<tr>
<td>Alternative attractiveness</td>
<td>+40.9%*</td>
<td>t=35.441; p&lt;.01</td>
<td>+33.2%</td>
</tr>
<tr>
<td>Alternative attractiveness * Task progression</td>
<td>+12.6%</td>
<td>t=9.214; p&lt;.01</td>
<td>+39.0%</td>
</tr>
<tr>
<td>Alternative attractiveness * Task experience</td>
<td>+12.3%</td>
<td>t=6.362; p&lt;.01</td>
<td>+8.7%</td>
</tr>
<tr>
<td>Attribute importance</td>
<td>+25.4%</td>
<td>t=40.867; p&lt;.01</td>
<td>+16.4%</td>
</tr>
<tr>
<td>Attribute importance * Task progression</td>
<td>+15.7%</td>
<td>t=13.384; p&lt;.01</td>
<td>-3.8%</td>
</tr>
<tr>
<td>Attribute importance * Task experience</td>
<td>+6.2%</td>
<td>t=5.478; p&lt;.01</td>
<td>+5.8%</td>
</tr>
<tr>
<td>Feature utility</td>
<td>-2.8%</td>
<td>t=-4.777; p&lt;.01</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Feature utility * Task progression</td>
<td>0%</td>
<td>t=-0.023; p=0.981</td>
<td>-4.2%</td>
</tr>
<tr>
<td>Feature utility * Task experience</td>
<td>-2.4%</td>
<td>t=-2.100; p=0.636</td>
<td>-3.5%</td>
</tr>
<tr>
<td>Task progression</td>
<td>-5.2%</td>
<td>t=-4.395; p&lt;.01</td>
<td>-6.6%</td>
</tr>
<tr>
<td>Task experience</td>
<td>-23.7%</td>
<td>t=-8.035; p&lt;.01</td>
<td>-25.5%</td>
</tr>
<tr>
<td>Horizontal centrality</td>
<td>+9.5%</td>
<td>t=14.753; p&lt;.01</td>
<td>+7.6%</td>
</tr>
<tr>
<td>Alternative first fixated</td>
<td>+13.5%</td>
<td>t=9.536; p&lt;.01</td>
<td>+25.6%</td>
</tr>
<tr>
<td>Task difficulty</td>
<td>+6.1%</td>
<td>t=3.316; p&lt;.01</td>
<td>+2.2%</td>
</tr>
</tbody>
</table>

* Read: One standard deviation shift in the attractiveness of an alternative increases the number of fixations by 40.9%.
Web appendix 1 – 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 1280x1024 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 has a best accuracy of 0.4° of visual angle and a sampling rate of 120 Hz. As in study 1, 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 are using 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 supposed 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 decided to 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 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 first 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, in future research studies we recommend the use of 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 had to choose the best vacation package in each choice task. 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 2 – Utility Estimates

In this appendix we provide 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:

\[
A1 \quad U_{cjt} = \beta_{c0} + \sum_{k \in j} \beta_{ck} + \epsilon_{cjt}
\]

where \( \beta_{c0} \) 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. \( \beta_{ck} \) denotes the utility of feature \( k \) that consumer \( c \) receives when choosing object \( j \). The last term in this equation, \( \epsilon_{cjt} \), 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 \( \epsilon_{c0t} \) 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 \( \beta_c \) 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 \( \beta_c \) be distributed according to a \( MVN(\theta, \Lambda) \) distribution. The parameter \( \theta \) determines the mean valuation across consumers while the variance covariance matrix \( \Lambda \) 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:
\( \theta \sim \text{MVN}(0, 10^2), \Lambda \sim \text{Inverse Wishart}(K + 5, \Sigma) \), where \( K \) is the number of rows of \( \Lambda \) and \( \Sigma \) is equal to the following matrix for Study 1:

\[
\begin{bmatrix}
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 & 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 & 0.00 & 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 & 0.00 & 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 & 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 & 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 & 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 & 0.00 & 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 & 0.00 & 0.00 & 0.00 & -0.50 & -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 & 0.00 & 0.00 & 0.00 & 1.33 & 0.00 & 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 & 1.33 & -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 & 0.00 & 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 & 0.00 & 0.00 & 0.00 & -0.50 & 1.50 & -0.50 & -0.50 & -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 & 0.00 & 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 & 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 & 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 & 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 & 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 & 0.00 & 0.00 \\
\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 chosen alternative 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.
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)=0.240 seconds; std err=0.133) are on average significantly longer than fixations to the left (M(left)=0.231 seconds; std err=0.131; t(right, left)=3.249; p<.001) and to the middle alternative (M(middle)=0.230 seconds; std err=0.136; 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)=0.511; p=0.61).

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 milliseconds). 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.
Figures and Tables in the Web Appendix

Figure A1: Simulation Results – Average Fixation Durations for the Left, Middle and Right Alternative When Excluding Fixations

Table A1: Fixations and Choices by Horizontal Position (Study 2)

<table>
<thead>
<tr>
<th></th>
<th>Left Alternative</th>
<th>Left from the Center Alternative</th>
<th>Center Alternative</th>
<th>Right from the Center Alternative</th>
<th>Right Alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of fixations</td>
<td>21.0%</td>
<td>24.1%</td>
<td>22.1%</td>
<td>18.9%</td>
<td>13.9%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(0.019)</td>
<td>(0.009)</td>
<td>(0.015)</td>
<td>(0.019)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Percent chosen</td>
<td>20.1%</td>
<td>18.4%</td>
<td>20.7%</td>
<td>23.4%</td>
<td>17.4%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(0.074)</td>
<td>(0.058)</td>
<td>(0.108)</td>
<td>(0.093)</td>
<td>(0.056)</td>
</tr>
</tbody>
</table>
Table A2: Fixations and Choices by Horizontal Position (Study 3)

<table>
<thead>
<tr>
<th></th>
<th>Left Alternative</th>
<th>Left from the Center Alternative</th>
<th>Right from the Center Alternative</th>
<th>Right Alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of fixations</td>
<td>22.6%</td>
<td>30.2%</td>
<td>27.7%</td>
<td>19.5%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(0.078)</td>
<td>(0.067)</td>
<td>(0.069)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Percent chosen</td>
<td>20.9%</td>
<td>22.3%</td>
<td>30.4%</td>
<td>26.4%</td>
</tr>
<tr>
<td>Standard error</td>
<td>(0.228)</td>
<td>(0.200)</td>
<td>(0.254)</td>
<td>(0.217)</td>
</tr>
</tbody>
</table>
Table A3: Multilevel Analysis of Factors Influencing Fixations in Three Studies (Beta Coefficients and Cell-level Model; * p<0.05, **p<0.01, *** p<0.001)

<table>
<thead>
<tr>
<th>Study Term</th>
<th>Coffee maker</th>
<th>Beach Vacation</th>
<th>Laptop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Term</td>
<td>Coefficient</td>
<td>Standard error</td>
<td>Coefficient</td>
</tr>
<tr>
<td><strong>Fixed effects coefficients</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alternative attractiveness</td>
<td>.343***</td>
<td>.010</td>
<td>.287***</td>
</tr>
<tr>
<td>Alternative attractiveness * Task progression</td>
<td>.119***</td>
<td>.013</td>
<td>.329***</td>
</tr>
<tr>
<td>Alternative attractiveness * Task experience</td>
<td>.116***</td>
<td>.018</td>
<td>.084***</td>
</tr>
<tr>
<td>Attribute importance</td>
<td>.226***</td>
<td>.006</td>
<td>.152***</td>
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<tr>
<td>Attribute importance * Task progression</td>
<td>.146***</td>
<td>.011</td>
<td>-.038***</td>
</tr>
<tr>
<td>Attribute importance * Task experience</td>
<td>.060***</td>
<td>.011</td>
<td>.057***</td>
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<tr>
<td>Feature utility</td>
<td>-.028***</td>
<td>.006</td>
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<tr>
<td>Feature utility * Task progression</td>
<td>.000</td>
<td>.011</td>
<td>-.043***</td>
</tr>
<tr>
<td>Feature utility * Task experience</td>
<td>-.024**</td>
<td>.012</td>
<td>-.036**</td>
</tr>
<tr>
<td>Task progression</td>
<td>-.054**</td>
<td>.012</td>
<td>-.068***</td>
</tr>
<tr>
<td>Task experience</td>
<td>-.270***</td>
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<td>-.295***</td>
</tr>
<tr>
<td>Horizontal centrality</td>
<td>.182***</td>
<td>.012</td>
<td>.073***</td>
</tr>
<tr>
<td>Alternative first fixated</td>
<td>.127***</td>
<td>.013</td>
<td>.228***</td>
</tr>
<tr>
<td>Task difficulty</td>
<td>.059***</td>
<td>.018</td>
<td>.022</td>
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<tr>
<td><strong>Random effects variances</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task nested within respondents</td>
<td>.169***</td>
<td>.011</td>
<td>.186***</td>
</tr>
<tr>
<td>Respondents</td>
<td>.157***</td>
<td>.032</td>
<td>.157***</td>
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<tr>
<td><strong>Model fit</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Log likelihood</td>
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<td>-33755.473</td>
<td>-122103.944</td>
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<tr>
<td>Number of observations</td>
<td>25920</td>
<td>18240</td>
<td>67200</td>
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