# The Multi-Attribute Attentional Drift Diffusion Model of Consumer Choice

Geoffrey Fisher
California Institute of Technology
gfisher@caltech.edu

Antonio Rangel
California Institute of Technology
rangel@hss.caltech.edu

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**Abstract**

Many choices consumers face are over outcomes that consist of multiple attributes. For instance, when deciding to purchase a particular product consumers must account for both its price and its brand. Although these choices are quite common, we know relatively little about how changes in consumer attention to specific attributes impacts decisions. We propose a new computational model, the multi-attribute attentional drift diffusion model (maDDM), that describes how consumers weight a product's attributes when making a decision. The model makes predictions about how changes in the amount of attention deployed to different attributes affects choices. In a laboratory experiment that makes use of eye tracking, we test and find evidence for these predictions. The model also predicts the existence of an attentional bias in multi-attribute choice: consumers increase the weight of the currently attended attribute and decrease the weight of unattended attributes. This bias affects decisions and has important implications for consumer science.

*Keywords*: Attentional Biases, Multi-attribute Choice, Value Estimation, Eye Tracking

A key open question in marketing involves understanding the processes consumers engage in as they estimate the value of products they plan to purchase. An understanding of this process could lead to more individually tailored policies that highlight particular attributes of a product while depressing others, ultimately helping consumers make better purchasing decisions. Furthermore, a deeper knowledge of this process may aid firms in both improving sales projections and better estimating the likelihood that an individual consumer will opt to purchase a particular product. Deeply ingrained in this topic is the extent to which attention to particular features of a choice affect how consumers perceive value. For instance, how does differential attention to positive and negative features of a product affect the decision of whether or not the consumer decides to purchase the product?

Take, for example, a grocery shopper deciding whether or not to purchase a particular food to consume later this week. Such a product, the food, can be described by a large number of attributes: how tasty the food is, how healthy it is, the quantity of specific nutrients in it, how well liked its brand is, its price, etc. In order to decide whether to purchase such a product, consumers must first estimate certain subjective attributes and then weight attributes in order to perceive the item's value. A favorable estimation of value would lead the consumer to purchase the food while an unfavorable estimation would result in the consumer moving on without purchasing the product.

In this paper, we estimate a biologically plausible and computational model, inspired by the neuroeconomics literature, which describes a simple version of how such a multi-attribute estimation process might occur. Our model, the multi-attribute attentional drift diffusion model (maDDM), details the choice process itself by modeling how attending to attributes, at the level of random eye fixations, alters consumers' value estimates of products. Importantly, our results provide a quantitative estimate for how attending to particular features of a product alters the weight those attended features receive when estimating value. This allows consumer scientists to better understand both the process people engage in as they attend to different attributes of a product and what about the value estimation process changes as consumers attend to different features.

To test our model, we design a simple laboratory experiment that makes use of eye tracking data to record what attributes in the decision environment consumers are attending to. In every trial, participants see a bundle that consists of two foods on the computer screen in front of them and are asked whether they are willing to take at least three bites from each of the two foods at the end of the experiment, responding "yes" or "no." Importantly, we know how much each subject enjoys each individual food in the bundle, so we always construct bundles where one food is appetitive and the other is aversive. In this sense, each bundle of foods consists of two attributes: a positive, appetitive attribute and a negative, aversive one.

To test whether our model can accurately describe the consumer choice process in this environment, we fit the model to a portion of the data and then test the predictions of our model on a different subset of data. Ultimately, we report evidence that our model fits well in terms of making accurate predictions about when consumers choose to eat the bundle, how long it takes to make those choices, and what they attend to throughout the choice process. Importantly, we find evidence of a fixation bias during choice: consumers both increase the weight of attended features and decrease the weight of unattended features when estimating value. This bias has important implications for consumer science.

The paper proceeds as follows. First, we discuss the most relevant literature to both our model and the underlying questions of how consumers make multi-attribute choices. This work includes research at the intersection of marketing, psychology, and neuroeconomics. We next describe the model we fit and explain how the computational process we have in mind is quantitatively carried out. After describing our laboratory experiment and empirical findings, we conclude by interpreting these particular findings and suggesting several future research directions.

## *Background Literature*

A large literature, from multiple disciplines, studies the processes consumers engage in as they estimate the value of a product with multiple attributes. In this section, we describe closely related work from marketing, neuroeconomics, and psychology in order to better frame our underlying question and its potential impact.

The most closely related literature to our proposed model is work from classic drift-diffusion models (DDM) of binary choice, where the consumer must decide to choose one of two available options that are often perceptual in nature (Luce 1986; Stone, 1960; Ratcliff, 1978; Ratcliff et al., 2003; Ratcliff & Smith, 2004; Laming, 1979; Link, 1992; Link, 1992; Smith, 1995; Smith, 2000). One well-known example of a task from this literature is a dot motion task (Gold and Shadlen, 2007). Here, a participant sees a video depicting a large number of dots on a computer screen in front of them. A portion of the dots move to the left side of the screen and another portion move to the right side. The task is to then decide the direction that the majority of the dots are moving. The difficulty of this task can be altered by changing the fraction of dots that move to one side versus the other. Roughly, the theory underlying these DDM models is that evidence for a response is stochastically integrated over time. Once the evidence has passed a particular decision threshold, a choice is then made. Hence, these models not only make predictions about choice, but also make predictions about how long it takes to make such a choice, which we refer to as reaction time.

In addition to providing a quantitatively accurate prediction of both choices and reaction times, a growing body of evidence from neuroscience has found that the implementation of these DDM models is biologically plausible. For instance, the lateral intraparietal area implements perceptual based computations consistent with the DDM (Britten et al., 1992; Gold and Shadlen, 2007; Heekeren et al., 2008). Furthermore, a number of studies have found evidence for these types of processes in value-based choice (Rangel and Clithero, 2013). Specifically, Basten et al. (2010) and Hare et al. (2011) both find that particular areas of the brain satisfy required properties of the DDM algorithm needed for value comparison.

Recently, the neuroeconomics literature has adapted these models to not only fit value-based choice, but also model the value estimation process at the level of eye fixations to multiple options (Krajbich et al., 2010; Krajbich & Rangel, 2011; Krajbich et al., 2012). This model is referred to as the attentional drift diffusion model (aDDM) and has been shown to explain decisions with two or three choice options, as well as simple purchasing decisions (see Fehr & Rangel, 2011, for a summary). The key idea of this model is that fixations to different options bias the evidence integration process in favor of the fixated item. In turn, this integration bias directly leads to a choice bias: items that are fixated on more are then more likely to be chosen. In this paper, instead of concerning ourselves with consumer choice over multiple products, we ask how consumers estimate the value of a single product that has two salient attributes. Essentially, consumers face a list of two attributes and will decide whether or not they are willing to consume the single good. In our model, fixating to an attribute will lead to an increased weight for that attribute when perceiving the value of the good. The precise quantitative model that we fit to the data is explained in the following section. While the existing aDDM literature has explained a number of previous choice scenarios, ours is the first to integrate eye fixation data and formally model a multi-attribute choice problem.

Existing work in DDMs is not the only literature that attempts to model a dynamic choice process. For instance, decision field theory (DFT) is a cognitive model of decision-making designed to understand how preferences evolve over time in order to reach a decision (Busemeyer et al., 1993). Critically, DFT applies to both multi-alternative and multi-attribute choice settings, and can account for a large number of phenomena, including the relationship between choice and reaction time, buying and selling price, and preference reversals (Busemeyer & Townsend, 1992; Roe et al., 2001; Busemeyer & Diederich, 2002; Diederich, 1997). Like the DDM approach, DFT operates through a diffusion process where value is determined over time; however, in DFT each option produces its own valence which is then integrated over time to produce a preference state. Once a preference state reaches a particular threshold, the process is terminated and a choice is made. In addition to DFT, a number of other dynamic process models attempt to explain typical context phenomena in choice such as the leaky competing accumulator (Usher & McClelland, 2001) and the multi-attribute linear ballistic accumulator (Trueblood et al., 2014).

While both the aDDM and DFT attempt to explain the underlying choice process that consumers engage in, we note the two literatures have progressed slightly differently. For instance, previous work on the aDDM has investigated how attention and the value estimation process change as a function of eye fixations to different options (Krajbich et al., 2010). Alternatively, DFT has instead modeled attention by appealing to a dynamic attention function that weights information over time (Roe et al, 2001; Diederich, 1997).

DFT's approach does not rely on eye tracking data and hence, does not model the effect of individual fixations on value estimation. On the other hand, the DFT approach does have certain benefits. For instance, DFT develops a deep understanding of both multi-attribute choice and choices over multiple options. In contrast, the aDDM has only been extended to choice over a small number of available options and has not modeled multi-attribute choice. Our work attempts to unify these two existing literatures. Specifically, we extend the underlying principles of the aDDM to a case of simple multi-attribute choice. In this sense, we allow our model to describe situations that DFT currently describes, yet we are also are able to model the effect of individual fixations on value perception. This approach allows us to relate eye fixations to consumer choice and understand how fixations affect value estimation under a dynamic model of consumer preference formation.

In addition to process-based models that describe how preferences are formed, a growing literature has sought to test the validity of different psychological theories through process-tracking data. Testing theories with process-tracking data allows one to learn more about the choice process itself, as certain theories may make accurate predictions about choice but fail in terms of process predictions (Payne et al., 1993). For instance, Willemsen et al. (2011) and Johnson et al. (2008) use MouselabWeb to test process-based predictions of models of risky choice. MouselabWeb records the order and duration of mouse movements to different features on a computer screen, providing the data necessary to tease apart different theories of preferences from one another (Johnson and Willemsen, 2014). This work helps determine whether there is evidence for proposed theories not only in choice data, but also in how consumers carry out the choice process.

In psychology and marketing, a number of papers have previously used eye tracking to study consumer decision-making. Russo and Rosen (1975) and Russo and Dosher (1983) study multi-alternative and multi-attribute choice using eye tracking data. They find that that feature-by-feature comparison makes up a large portion of the decision procedure. Chandon et al. (2008) analyzed commercial eye tracking data that was collected for hypothetical retail shelves. They found attentional fixations were driven more by packaging than price, suggesting an attribute-based tradeoff towards packaging. Van der Lans et al. (2008) used eye tracking data to study how brand information was detected by consumers within a display; however, no choices were made in the experiment. Stüttgen et al. (2012) and Shi et al. (2013) also relate eye movements to decision making.

Furthermore, several papers in marketing have previously utilized drift diffusion models, including Satomura et al. (2014) and Philiastides and Ratcliff (2013), though this work in marketing has not integrated these models with eye tracking data. Finally, although conjoint analysis has been extremely influential in marketing research, it typically attempts to understand which attributes are most influential on consumer choice (Green and Srinivasan, 1978; Green et al., 1981; Srinivasan, 1988); meanwhile, our work is focused on the underlying processes that occur when estimating the value of products as consumers attend to different attributes. Our work complements this literature by empirically modeling the process of how a fixation to an attribute affects the estimated value of a good.

## *Model Description*

To set up the scenario for our theory and experiment, consider the following simple choice: a consumer is shown a product that has two attributes, and must make a "yes" or "no" decision regarding whether it will be consumed. Importantly, the product has only two attributes that the consumer cares about. One of these attributes is positive and enjoyed by the consumer, the other is negative and disliked by the consumer. For instance, one may think of the positive attribute as a well-liked brand and the negative attribute as a high price of the product. Next suppose that consumers weight the two attributes in order to estimate the value of the product. Here, we can say

$$R = \beta_0 + \beta_P R_P + \beta_N R_N$$

where $R$ is the estimated value of the product, $R_P$ is a rating of how much the consumer enjoys the positive attribute, $R_N$ is a rating of how much the consumer dislikes the negative attribute, and $\beta_i$ is an attribute-specific weight that is used to weight attribute ratings.

In our model, the maDDM, a relative decision value (RDV) signal is integrated over time until enough evidence is gathered that the signal crosses a threshold and the binary choice, “yes” or “no,” is made. Importantly, like the previously described attentional drift diffusion model, we allow for fixation biases to affect how value is estimated. In this case, a fixation bias implies that attending to a particular attribute increases the weight that attribute is assigned when estimating value. Likewise, the non-fixated attribute can receive a decrease in the weight it receives. Specifically, when looking at the positive attribute the RDV evolves according to:

$$V_t = V_{t-1} + d(\beta_0 + \delta\beta_P R_P + \theta\beta_N R_N) + \varepsilon_t$$

and when looking at the negative attribute, it evolves according to:

$$V_t = V_{t-1} + d(\beta_0 + \theta\beta_P R_P + \delta\beta_N R_N) + \varepsilon_t.$$

In the above, $V_t$ is the value of the RDV at time $t$, $d$ is a constant that controls the speed of integration (in units $ms^{-1}$), $\delta$ is a parameter that can take values greater than or equal to 1 and reflects the fixation bias to the fixated attribute, $\theta$ is a constant between 0 and 1 that reflects a fixation bias to the non-fixated attribute, and $\varepsilon_t$ is white Gaussian noise with variance $\sigma^2$ that reflects the stochastic nature of the process. The RDV terminates when the RDV signals crosses an upper-barrier at $B = 1$, which corresponds to a “yes” decision, or a lower barrier at $B = -1$, which corresponds to a “no” decision. The time $t$ at which the barrier is crossed corresponds to the reaction time of the choice, measured in milliseconds.

A fixation bias in our model occurs when $\delta > 1$ or $\theta < 1$. In such a scenario, attending to the positive attribute biases the consumer in favor of consuming the item while attending to the negative item biases the consumer in favor of choosing the not consume the item. Such a bias directly alters the RDV by adjusting the weights of each attribute: the weight of the attended attribute is increased while the weight of the unattended attribute is decreased. Note how when $\delta = \theta = 1$, there is no fixation bias and hence, the value integration process evolves at the same rate regardless of the attended attribute.

Figure 1 depicts how a decision is reached in the maDDM with a fixation bias. Here, the consumer makes three fixations to the different attributes, and then responds “yes.” Note, that as a result of the fixation bias, the RDV is biased towards the attribute that is currently attended. In other words, the RDV moves toward the “no” barrier when the consumer attends to the negative attribute, and it moves towards the “yes” barrier when the consumer attends to the positive attribute.

Importantly, the model assumes that the fixation process between the two attributes is independent of each individual attribute’s value. The first fixation goes to the left attribute with probability *p*. Fixations then alternate between the two attributes until a barrier is crossed. At the beginning of each fixation, a maximum fixation length is drawn from a distribution that depends on the type of attribute (positive or negative) and the difficulty of the decision, which is largest when consumers are indifferent between responding “yes” and “no.” The fixation runs its course unless a barrier is crossed before it terminates, which ends the choice process.

A key issue we will address in this paper is the quantitative extent to which a fixation bias alters value estimation. From our experiment, we are able to estimate $\delta$ and $\theta$ and show that although relatively small in size, a significant fixation bias is present in the data. We describe our experiment designed to estimate and test the predictions of the maDDM in the next section.

## *Experiment Methods*

Forty-six subjects from the Caltech Brainscience subject pool participated in the experiment. All subjects had normal or corrected-to-normal vision with the use of either contact lenses or glasses. Subjects were required to fast for four hours before the start of the experiment. Before subjects were allowed to enter the lab, they had to verbally confirm to the experimenter the last time they consumed food. Participants were paid a $5 show-up fee and received an additional $25 upon successful completion of the experiment. The California Institute of Technology Institutional Review Board approved the experiment.

The experiment consisted of three tasks, summarized in Figure 2. Although subjects knew there would be three sections, they did not know what each section would be until immediately before they took part in it. In other words, subjects read the instructions for the first section and completed it on the computer, then read the instructions for the second section and completed it on the computer, etc.

In Rating Task 1, subjects performed a liking-rating task over individual foods seen on the computer screen in front of them. Each food was depicted with a high-resolution picture and subjects had as long as they liked to enter a rating. Ratings were made on an integer scale from -3 to 3 in response to the question "How much would you enjoy that particular food at the end of today's experiment?" These ratings were entered using the bottom row of the keyboard. A total of thirty unique foods were rated, and each subject rated each food twice in a randomized order for a total of sixty trials. Of these thirty foods, eighteen were previously rated as appetitive (images taken from Plassmann et al., 2007) and twelve were previously rated as aversive (images taken from Plassmann et al., 2010). A list of all foods used in the experiment is contained in the Appendix. For every food, we computed the average value it was rated by each subject. Foods that were rated larger than zero were classified as "positive," foods that were rated less than zero were classified as "negative," and foods that had an average rating of zero were omitted from the remaining tasks.

In Rating Task 2, subjects saw bundles of two foods on the screen and made liking ratings over the bundles. Participants had as long as they liked to give a rating of the bundle and saw each bundle only once. Every bundle contained one positive food and one negative food from the previous round. The number of trials in this section depended on the number of subject-specific foods in both the positive and negative categories; subjects were asked to rate every potential pair of one positive and one negative food. Ratings were elicited from -3 to 3 in were in response to the question "How much would you enjoy taking at least three bites from both of the foods on the screen?"

In the Choice Task, the final section, subjects saw a subset of the bundles they previously made ratings over and made a binary choice about whether they were willing to take at least three bites from each of the foods at the end of the experiment. These ratings were entered with the subject's dominant hand using the index and middle fingers. Pressing the "v" key meant "yes," they were willing to eat the two foods, and pressing the "b" key mean "no," they were not willing to eat the two foods. Participants in this section made two hundred such choices. Throughout the task, eye movements were recorded at 500 Hz using a desktop mounted SR research Eyelink 1000 eye tracker. The eye tracker was calibrated immediately after reading the instructions for this choice task. Subjects were instructed that at the end of this task, they would need to remain in the lab for an additional twenty minutes. During those twenty minutes, one of the two hundred trials they made decisions over would be chosen at random and implemented. If on that randomly selected trial the subject chose “yes,” then they would have to eat at least three bites from each of the foods in the bundle that they agreed to eat; however if the subject chose “no,” they would still need to remain in the lab for twenty minutes but would not be allowed to eat anything. This procedure encouraged subjects to give incentive compatible responses. After the experiment was complete, subjects completed a brief questionnaire, were paid their experimental earnings, and then permitted to leave.

## *Results*

### *Model Description*

The maDDM can describe the choice process in this task. Here, the value the consumer estimates is the difference between the value of consuming the bundle of foods seen on the screen, $R_B$, and the value of not eating anything, $R_0$. From the instructions given in our task, $R_0 = 0$, as subjects were instructed to give a rating of zero to the bundles of foods that they were indifferent between consuming and not consuming.

The value of the bundle, $R_B$, can be calculated as a weighted sum of the value of the positive food, $R_P$, and the value of the negative food, $R_N$. To calculate these weights, we estimate the equation

$$R_B = \beta_0 + \beta_P R_P + \beta_N R_N$$

by regressing $R_B$ from the second task on the values of $R_P$ and $R_N$ from the first task for each subject (mean $\beta_0 = 0.59$, SD = 2.17; mean $\beta_P = 0.61$, SD = 0.40; mean $\beta_N = 0.99$, SD = 0.74). Importantly, in our task the unit of the good consumers make choices over is the bundle rating, but the unit of the attribute is individual liking rating of each food. Both these quantities are experimentally elicited. Note how the nature of the experiment, with one positive and one negative attribute, prevents any interaction effects among attributes when deciding to consume the bundle.

Next, we add parameters to allow for a fixation bias in the RDV. When looking at the positive food, the RDV evolves according to

$$V_t = V_{t-1} + d(\beta_0 + \delta\beta_P R_P + \theta\beta_N R_N) + \varepsilon_t$$

and when looking at the negative food, it evolves according to

$$V_t = V_{t-1} + d(\beta_0 + \theta\beta_P R_P + \delta\beta_N R_N) + \varepsilon_t.$$

The model works precisely as described earlier. In the next section, we describe how we fit the model to the data.

*Model Fitting*

To fit the model, we first split the data from the third task into even and odd numbered trials for every subject. We next fit the even numbered trials of the group data using maximum likelihood estimation (MLE) on the observed choices and reaction times. The estimation procedure was conducted as follows.

We fit the model at the group level to both choice and reaction time data for all 46 subjects by pooling all even numbered trials into a single data set. As our model requires a large amount of data to estimate the parameters of interest, fitting at the individual level would result in highly noisy estimates. We next implemented a maximum likelihood estimation procedure to estimate the parameters of the best fitting maDDM. For each of the 7 possible bundle-liking ratings, we ran 5,000 simulated trials of the model. Each simulation was conducted as follows. Individual liking ratings for both the positive and negative food were drawn from the empirical distribution of liking ratings conditional on the rating of the bundle. The regression weights, $\beta_0$, $\beta_P$, and $\beta_N$, were drawn from the subject-estimated weights associated with the randomly selected simulated liking ratings.

In our simulated trials, we randomly sample fixations lengths dependent on both the bundle liking rating and whether the fixation is to either the positive or negative food. In our data, subjects first looked to the left item 68% of the time, which we apply to the simulations. Additionally, in each simulation we randomly determine whether the positive or negative item appears on the left or right side of the simulated screen. First fixations were sampled separately from middle fixations and were independent of bundle value, but dependent upon the individual liking rating of the food. Although our model assumes that fixations between the two items on the screen occur instantaneously, there are observed saccade length transitions in each trial. To take this into account, in every simulated trial we randomly sample from the empirical distribution of transition times and add that sampled transition time to the simulated total fixation time. This sum represents the simulated reaction time in a trial.

Next, in the simulated data for each vector of parameters, we calculate the probability of an observation as follows. We create a matrix that has 14 columns, one for each bundle liking rating and simulated choice, and rows where each row is a 100 ms interval and the maximum row of the matrix is for a reaction time larger than 7500 ms. Next, we fill in this matrix with the number of observations in each row by column. We then compute the probability of an observation in each cell by dividing the number of observations per cell by the total number of observations in each bundle liking rating. We performed a similar classification exercise on the observed even-numbered data, except instead of calculating probabilities, we left the matrix with entries of the number of observations per cell. To compute the parameters that maximized the log-likelihood of the data, we took the logarithm of the simulated probabilities, multiplied by the number of data trials in each cell, and summed these values. In the event that a simulated probability was 0, we instead replaced this simulated probability with 1 / (2*number of simulations per bundle liking rating) = 1 / 10,000. We then normalized this probability by bundle liking rating. This sum assesses how well the model fits the data; larger values indicate the model fits better. The parameters that generate the largest sum are the MLE parameters we estimate.

In our main estimation procedure, we first did a coarse search over the following parameter space:

$$d \text{ in } \{0.0001, 0.0005, 0.001, 0.0015, 0.002, 0.0025\}$$

$$\sigma \text{ in } \{0.005, 0.01, 0.015, 0.02, 0.025, 0.03\}$$

$$\delta \text{ in } \{1, 1.05, 1.1, 1.15\}$$

$$\theta \text{ in } \{0.85, 0.9, .95, 1\}$$

and then conducted a finer grid search over the following parameter space:

$$d \text{ in } \{0.001, 0.0012, 0.0013, 0.0014, 0.0015, 0.0016, 0.0017\}$$

$$\sigma \text{ in } \{0.01, 0.0125, 0.015, 0.0175, 0.02, 0.0225\}$$

$\delta$ in {1, 1.025, 1.05, 1.075, 1.1, 1.125 1.15}

$\theta$ in {0.85, 0.875, 0.9, 0.925, 0.95, 0.975, 1}.

The best fitting model had parameters $d = 0.0014$, $\sigma = 0.0175$, $\delta = 1.025$, and $\theta = 0.925$ with a log-likelihood value of -18037.

We next fit two different types of no fixation bias models by setting $\delta = \theta = 1$. When $d = 0.0014$ and $\sigma = 0.0175$, the values of the best fitting model before, this model has a log-likelihood value of -18071. When the best fitting $d$ and $\sigma$ were estimated ($d = 0.0013$ and $\sigma = 0.02$) along with the restriction that $\delta = \theta = 1$, the model had a log-likelihood of -18053. Using a likelihood ratio test statistic, the best fitting model with an estimated fixation bias fits the data better than either of the no fixation bias models ($p < 0.001$ for comparison with either fitted no fixation bias model).

Additionally, we test the restriction of whether $\delta = \theta$. In this case, the best fitting model has $d = 0.00145$, $\sigma = 0.0175$, $\delta = \theta = 0.95$ with a log-likelihood value of -18045. Using a likelihood ratio test, our first model without such a restriction fits the data better ($p < 0.01$). These tests suggest strong evidence for a fixation bias that both increases the weight the attended attribute receives and decreases the weight the unattended attribute receives.

In the next several sections, we investigate how well the model is able to quantitatively predict the data. To do this, we use the best fitting model parameters to simulate the model 5,000 times for each bundle liking rating. To determine sampled fixation lengths we use the empirical distribution of observed fixations, which we allow to depend both on whether a fixation is to a positive or negative item and the bundle rating. The results of this exercise are described below. Note that in all comparisons of the model to the data, we compare the simulated model data to the odd-numbered trials from the data as we used the even-numbered trials to fit the data.

*Basic Psychometrics*

Figure 3 depicts the out of sample predictions of the model. First, the model accurately predicts the relationship between the liking rating of the bundle and the probability of agreeing to consume it: choices are a logistic function of this liking rating (goodness of fit test: $p = 0.71$).

The model also makes accurate predictions about reaction times. Specifically, reaction times were negatively correlated with the difficulty of the choice, i.e. the absolute value of the bundle rating ($p < 0.01$). Figure 3b depicts the typical inverted-U pattern of reaction time when plotted against the liking rating of the bundle.

Furthermore, while the model over-predicts the number of fixations made between attributes, the same general U-shaped pattern, where the number of fixations decreases with difficulty, is observed in the data ($p < 0.01$). This over-prediction of the number of fixations is an unavoidable feature of the model fitting process that we used, and also occurs if applied to synthetic datasets generated using the maDDM described above.

Together, these findings show that the maDDM is able to account for the basic psychometric properties of the choice process fairly well.

*Visual Search Process*

The model makes a number of assumptions about the fixation process. First, the probability that the first fixation was to the positive item was not significantly different than 0.5 as the side of the screen with the appetitive item was randomized each trial ($p > 0.05$). Second, although middle fixation length depended on whether the current fixation was to a positive or negative food, fixation length did not depend on the value of the fixated food (mixed-effects regression of middle fixation length on an indicator for whether the item is positive or negative and the liking rating of the item: slope for indicator = 21.18, $p > 0.5$; slope for rating = -21.23, $p < 0.01$). Essentially, fixations to negative items were longer than to positive items. Third, middle fixation lengths to either attribute depended on choice difficulty with respect to the absolute value of bundle liking rating (mixed-effect regression: slope = -21.63, $p < 0.01$). As described in the model fitting section, these empirical findings were taken into account in the estimation procedure.

Finally, the model assumes that fixations to the negative item will last longer than fixations to the positive item. Importantly the model makes this assumption for all three types of fixations: first, middle, and last. Figure 4 supports this assumption for all three cases ($p < 0.001$ for each of three tests between positive and negative fixation types).

The maDDM assumes that variation in the relative amount of time spent fixating to the positive attribute is random, and predicts that this affects how the two attributes are weighted in the decision. The results in this subsection show that these assumptions are consistent with the observed fixation patterns.

*Model Predictions*

The model makes several predictions about the relationship between choices and fixations that we test here.

First, the model suggests that the final fixation duration of a trial should be shorter than middle fixations; this finding is confirmed in the data (see Figure 5, $p < 0.001$). To see why the model makes this prediction, note that final fixations are terminated early as a result of the RDV crossing a barrier. We also find that first fixations are shorter than middle fixations. Although the model made no ex ante prediction about the relationship between these two types of fixations, such a prediction was incorporated into the model ex post through the fixation sampling procedure as described earlier.

Second, the model predicts a strong relationship between choices, time before the final fixation, and the duration of the final fixation. Specifically, the model predicts that excluding the last fixation, the more relative time that is spent attending to the positive item, the longer the last fixation will be to the negative item conditional on declining to eat the bundle. Here, relative fixation time to an item refers to the time in milliseconds spent fixating to that item divided by the total time spent fixating to any item on the screen in each trial. We test this prediction by regressing the duration of the last fixation in which "no" was chosen on the relative time advantage to the positive item excluding the last fixation (mixed effects regression: slope = 70.47, $p < 0.01$). Interestingly, the model does not make a similar prediction about the last fixation to a positive item. Specifically, it does not predict that excluding the last fixation, the more relative time that is spent attending to the negative item, the longer the last fixation will be to the positive item conditional on agreeing to eat the bundle.

*Choice Biases*

The model also predicts a number of attentional driven biases, when $\delta > 1$ and $\theta < 1$, that we test in this section.

First, the model predicts that, after controlling for bundle liking ratings, additional time spent attending to the positive attribute increases the probability of saying “yes” while additional time spent attending to the negative attribute decreases the probability of saying “yes." To test for this effect in our data, we run a mixed-effects logistic regression of choice on rating of the bundle, liking rating of the positive food interacted with relative time to the positive food, and the liking rating of the negative item interacted with relative time to the negative item. Our results, depicted in Figure 6a, support this prediction (bias = -.15, $p = .56$; slope for bundle liking rating = 1.14, $p < 0.01$; slope on positive liking rating x relative time attending to positive item = .23, $p = 0.0506$; slope on negative liking rating x relative time attending to negative item = -0.51, $p < 0.01$). To examine the size of this effect, suppose the bundle liking rating is 0, the positive attribute has a rating of 2, and the negative attribute has a rating of -2. These three ratings are close to the mean ratings across all subjects. Our estimate predicts that when a consumer spends 25% of the trial attending to the positive attribute, there is only a 31% chance of agreeing to consume the bundle; however, if that consumer instead spends 75% of the trial attending to the positive attribute, the probability of responding “yes” increases to 49%. In contrast, a model without a fixation bias does not make a prediction of this nature.

Second, the model predicts that the probability of choosing “yes” depends on the relative amount of time spent attending to the positive item rather than the negative item. A mixed-effects logistic regression of choice on the final relative time advantage spent attending to the positive item reveals this prediction holds in the data (slope = 0.38, $p < 0.01$), as depicted in Figure 6B. Here, an increase in time attending to the positive attribute from 25% to 75% corresponds to a probability increase from 0.37 to 0.47 for agreeing to consume the bundle. Again, a model without a fixation bias does not make this prediction.

Third, the model predicts that the longer the first fixation is to the negative (positive) item, the less (more) likely one is to agree to eat the foods. To see why, note that longer first fixations to the negative (positive) item greatly bias the RDV in favor of saying no (yes). To test this prediction, we first define a choice consistency variable that takes value 1 when the participant responded "yes" and the first fixation was to the positive item and also takes value 1 when the participant responded "no" and the first fixation was to the negative item; otherwise, this variable takes the value 0. A mixed effects regression of this consistency variable on the duration of the first fixation supports this prediction (slope = 0.00074, $p < 0.001$). To quantify the effect size, doubling the duration of the first fixation from 250ms to 500ms increases the probability of making a choice consistent with attention to the first attribute from 0.51 to 0.56.

In a related result, any biases in the item that is attended to first should translate into choice biases. Figure 6c illustrates that when regressing the probability a subject looks at the positive food first on the average probability the subject agrees to eat the bundle in the experiment, we find that the two are positively correlated (slope = 0.09; $p < 0.05$).

Finally the model makes a prediction regarding the relationship between the last fixation and choice. Conditional on value of the bundle, when the last fixation is to the positive item the probability of choosing "yes" should be larger than when the last fixation is to the negative item. In the simulated data, we run a logistic regression of choice on a constant, the bundle liking rating, an indicator variable for when the last fixation is to the positive item, and the interaction of the bundle liking rating with the indicator variable. We find the interaction term is not statistically significant, but the indicator variable is significant suggesting the probability of agreeing to consume the bundle is larger when the last fixation is to the positive item than when the last fixation is to the negative item. However, the size of this difference is relatively small: the average difference over all seven bundle values is only estimated to be 7.6% (SD = 2.6%) higher when the last fixation is to positive item than the negative. Note that since the size of the bias coefficients are small (i.e., $\delta$ and $\theta$ are near 1), the predicted magnitude of this effect will also be small. To test this model prediction in the data, we estimate two mixed logistic regressions where the dependent variable differs on the location of the last fixation, and the independent variables include a constant and the bundle liking rating. We find no significant differences between either the intercept or the slope between each regression, though it is worth noting that the intercept's sign difference is in the model's predicted direction (slope when last fixation positive: 1.06, slope when last fixation negative: 1.17, intercept when last fixation positive: -0.38, intercept when last fixation negative: -0.51). As the size of this effect is predicted to be relatively small, we simply may not have enough power in our data to detect this prediction.

## *General Discussion*

Our results are a first step towards a better understanding of how eye fixations to attributes alters the value estimation process in multi-attribute consumer choice. First, we propose the maDDM that details how simple, multi-attribute consumer choices could be made. We next test predictions of our model in a laboratory experiment that makes use of eye tracking. Importantly, the maDDM is focused on the process of the decision itself, rather than solely on the outcome; hence, our model makes quantitative and testable predictions about the relationship between choices, reaction times, and attention to attributes.

We report the results of a laboratory experiment where participants decided whether or not to eat bundles of foods while their eye movements were recorded. Every bundle consisted of one positive, appetitive food and one negative, aversive food. After estimating the maDDM, we find evidence for a fixation bias in multi-attribute choice. Specifically, how value is dynamically estimated changes depending on the currently attended attribute. In our model, this change is related to the speed, or drift, of evidence accumulation in favor of either consuming or not consuming the product. Our data suggests consumers increase the attended attribute's weight by 2.5% and decrease the unattended attribute's weight by 7.5%. This fixation bias has important implications that affect consumer choice. For instance, we find that more time spent attending to the positive attribute increases the probability of consuming the bundle. Additionally, subjects who look first at the positive item are more likely to agree to consume the bundle even though there is randomness as to what attribute subjects first attend. These, among other findings, demonstrate that eye fixations to attributes impact choices in the way the maDDM predicts.

Our work differentiates itself from previous work in process-based consumer choice in a number of ways. First, while the existing aDDM literature has focused on understanding the role of fixations in multi-alternative choice (Krajbich et al., 2010; Krajbich & Rangel, 2011), it has remained silent as to how fixations affect attribute-based value estimation. Our model takes a first step towards understanding this process and extends the aDDM to this important consumer choice environment. Furthermore, while DFT has previously explored decision-making in multi-attribute environments, it has not incorporated eye fixations into understanding how attention to attributes affects the attribute's assigned weights (Busemeyer & Townsend, 1992; Roe et al., 2001; Busemeyer & Diederich, 2002; Diederich, 1997).

We find that minor attentional differences in a typical value estimation task can lead to significant differences in consumer perceptions. From this, our work connects to the marketing literature that attempts to understand the impact of visual cues on consumer behavior (Deng and Kahn, 2009; Hagtvedt and Patrick, 2008; Raghubir and Greenleaf, 2006; Scott, 1994; Cian et al., 2014). Importantly, our work differentiates itself from this literature in that we are concerned with the estimation process itself rather than whether cues bias decisions. Our work is more centered on how multiple attributes, displayed as images in our experiment, are used to estimate the value of a single product.

It is worth noting that in our paradigm we find much evidence that has a qualitative flavor of loss aversion. Specifically, the duration of a fixation to a negative attribute is on average longer than the duration to a positive attribute, consumers weight negative attributes more heavily than positive attributes in choices, and negative attributes are attended to for a longer period of time throughout the choice process. This differential attribute weighting is consistent with the literature on loss aversion (Kahneman & Tversky, 1984; etc) while the differences in fixations to attributes are consistent with previous process tracking studies of loss aversion (Willemsen et al., 2011). This difference in fixation duration to the negative and positive attributes can be further explained given that the amount of time one attends to a feature appears to influence its weight (Willemsen et al., 2011; Schkade & Johnson, 1989; Fiske, 1980; Wedell & Senter, 1997), a finding we draw on throughout the paper.

A natural question about our model concerns the direction of causality between fixations and choice. Namely, while our model assumes that fixations bias the value estimation process, another possibility is that the value of the attributes, or products, directly affects the fixation process. The best way to address this question is through follow-up work that provides a causal test of this theory. While we are currently working on such studies, a number of related papers address the issue in different contexts. For instance, Fisher and Rangel (2014) find that exogenously varying attention to attributes in an intertemporal choice task affects behavior; they find that increasing the time one attends to monetary amounts, rather than the delays those monetary amounts would be received, increases the probability the delayed outcome is chosen. Armel et al. (2008) bias attention in both food and poster choice and find that increasing the amount of time spent attending to an item increases the probability that item is chosen. Kim et al. (2012) find that preference reversals in risky choice are associated with differential attention to features of gambles, such as the probability of winning and monetary amounts that could be won. Furthermore, evidence from neuroeconomics suggests that an area of the brain, the ventromedial prefrontal cortex (vmPFC), encodes stimulus-dependent value signals (Padoa-Schioppa & Assad, 2006; Kable & Glmicher, 2007; Hare et al., 2008). Most relevantly to our causality question, Lim et al. (2011) find that the vmPFC encodes attention-modulated relative value signals, suggesting neurobiological evidence that fixations alter the value estimation process. While this literature speculates that there is a causal role from fixations to choice, we cannot rule out the possibility that causality also works in the other direction.

We conclude by observing two limitations of our work. First, the environment subjects are placed in is fairly artificial as they face a large number of trials with generic stimuli on a computer screen. Although it is not realistic for consumers to encounter such scenarios in real world environments, this highly stylized laboratory setting allows us to accurately estimate our proposed model. Specifically, in order to fit our model we need to observe a large number of choices so that precise parameter estimates can be pinned down. In turn, this provides an answer to our central question: does attention to attributes alter weights and affect value estimation. In future research, it would be useful to estimate a similar type of model in a more real-world environment, or even apply our model with estimated parameters to observable consumer purchasing choices. Such an exercise would help us understand how the observed attention bias in our data corresponds to consumer behavior in the real world.

A second limitation is that the number of attributes used in this study is relatively small; it's likely consumers care about more than two attributes. We have several comments regarding this point. As our goal was to identify and estimate a fixation bias in multi-attribute choice, it stands to reason we should take a first pass at this issue by utilizing a simple environment that we can, over time, further develop. Along this line, we have laid the groundwork for how such models may be estimated. Finally, we currently have several works in progress that extend this exercise to more than two attributes and more than one option.

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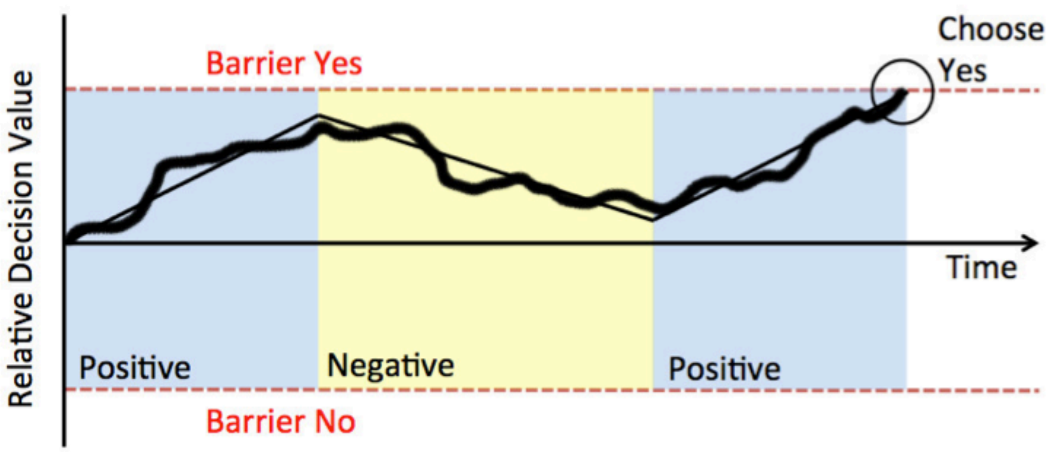
**Figure 1**

Depiction of the model. A relative decision value (RDV) signal evolves over time. Its slope is biased towards the fixated attribute, but random noise is added to the RDV at every millisecond. When the RDV hits a barrier, a decision is made. The shaded vertical regions represent what item is currently fixated. In this example, three fixations are made (positive, negative, positive) and the consumer chose "yes." The equations below the image describe how the RDV is integrated over time. The blue δ parameter describes an increase in weight that the attended item receives, while the red θ parameter describes a decrease in weight that the unattended item receives.




Look at Positive Attribute: $V_t = V_{t-1} + d(\delta\beta_P R_P + \theta\beta_N R_N + \beta_0) + \varepsilon_t$

Look at Negative Attribute: $V_t = V_{t-1} + d(\theta\beta_P R_P + \delta\beta_N R_N + \beta_0) + \varepsilon_t$

**Figure 2**

Experimental design. Subjects participated in three experimental tasks during one laboratory session. First, subjects participated in Rating Task 1 where they entered liking ratings for individual foods. Next they participated in Rating Task 2 where they entered liking ratings for bundles of foods where each bundle consisted of one positively rated food and one negatively rated food from Rating Task 1. Finally, subjects participated in the Choice Task where they made decisions over whether they were willing to take at least three bites from each of the two foods on the screen at the end of the experiment. The foods on the screen were chosen as bundles from Rating Task 2. Participants' eye movements were recorded as they made these choices. The timing of each screen is depicted at the bottom of the figure. Each subject saw a fixation cross for 500ms (this timing was enforced with the eye tracker in the Choice Task) and then had as long as they liked to enter a rating or make a choice. After doing so, they saw feedback of their rating or choice for 2000 ms and then moved onto the next trial.

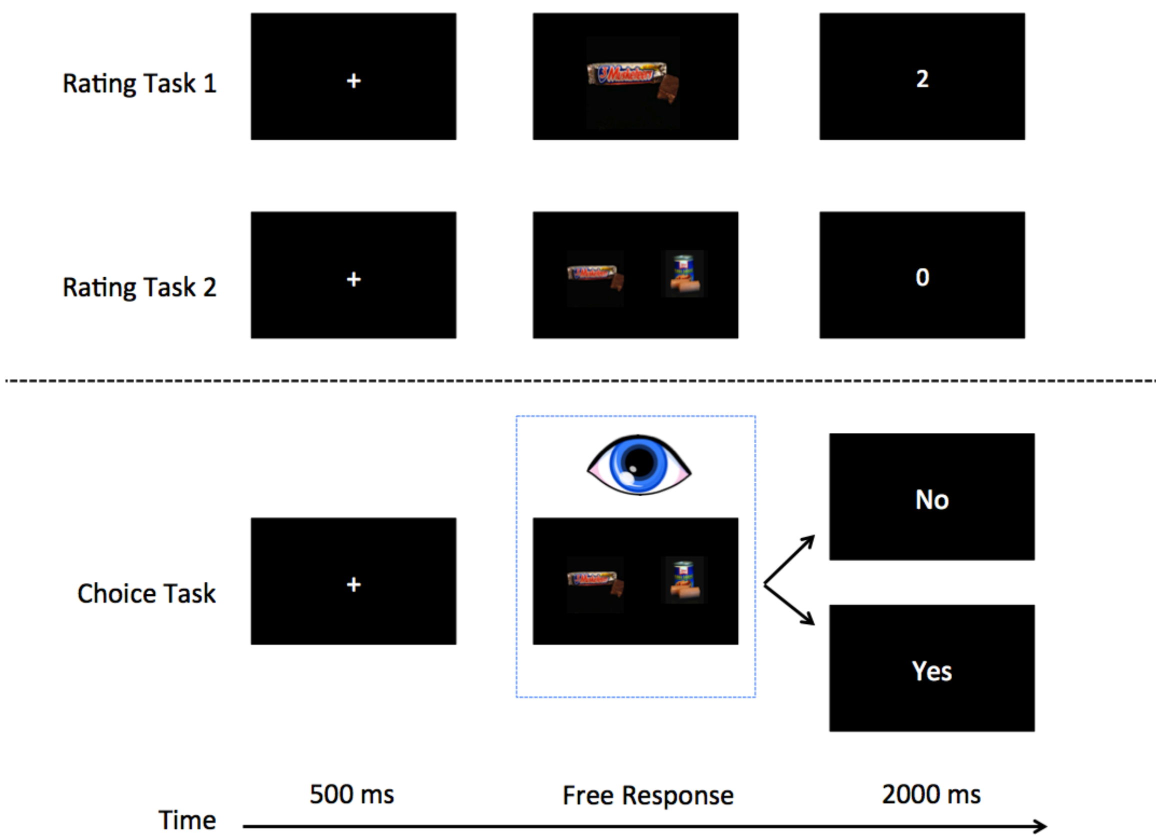


**Figure 3**

Basic psychometrics. (A) Psychometric choice curve with the liking rating of the bundle on the horizontal axis and the probability of agreeing to eat the bundle on the vertical axis. (B) Reaction times as a function of the liking rating of the bundle. (C) Number of fixations in a trial as a function of the liking rating of the bundle. Circles and vertical bars represent the odd numbered data, where standard errors are clustered by subject. Blue lines are the model simulations with thickness of the line indicating the size of the model standard errors.

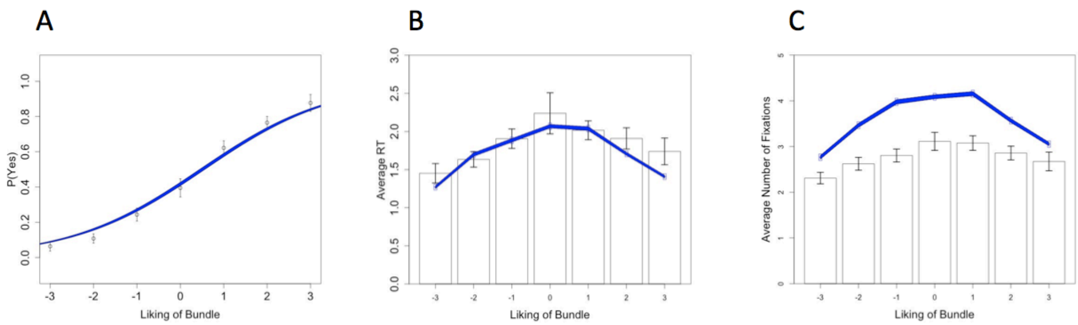


**Figure 4**

Visual Search Process. Difference in fixation durations to positive and negative items for each fixation type. An asterisk denotes a significant difference at $p < 0.01$. All standard errors clustered by subject.

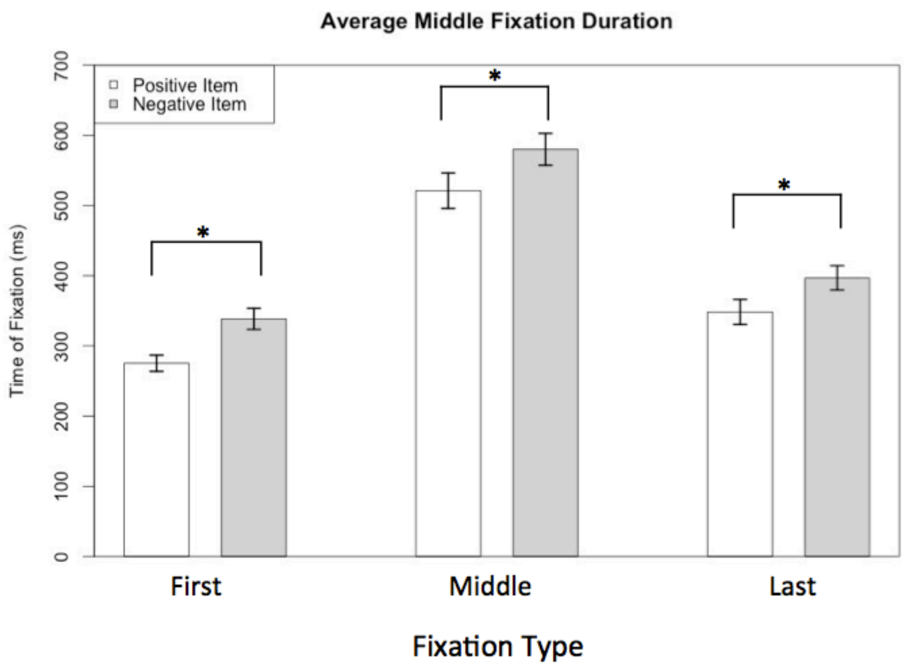


**Figure 5**

Model Predictions. Fixation duration by type of fixation. Middle fixations are fixations that are not first or last fixations. Standard errors clustered by subject.

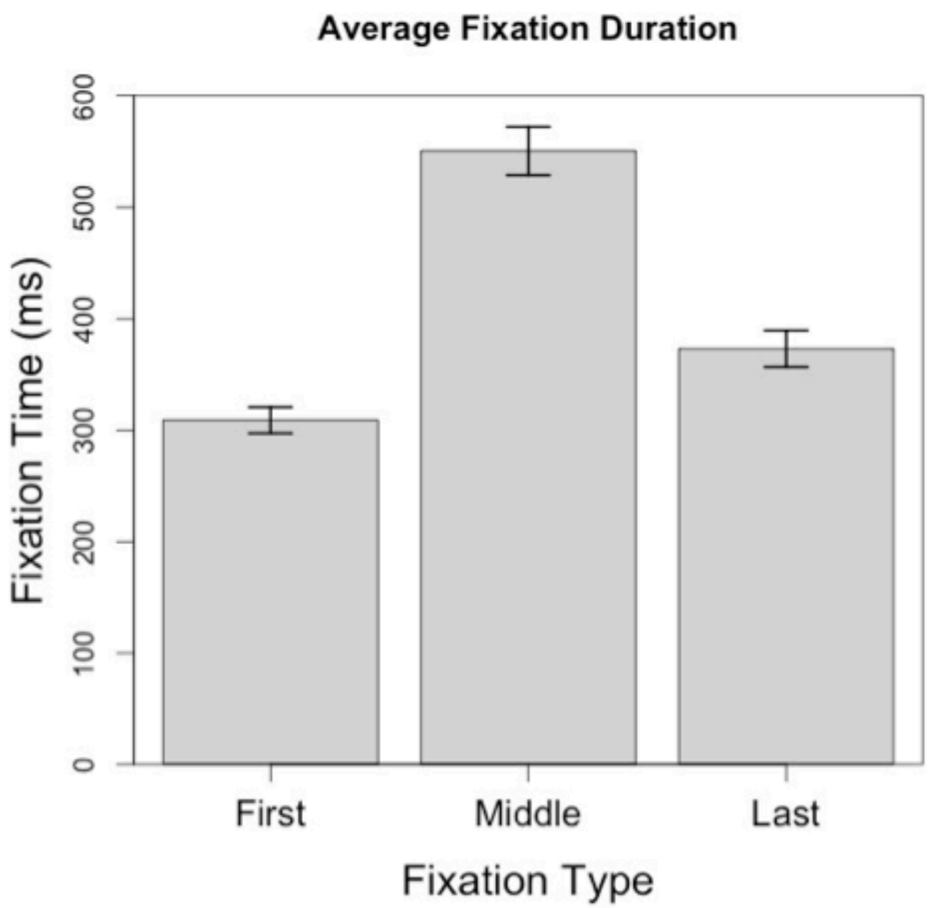
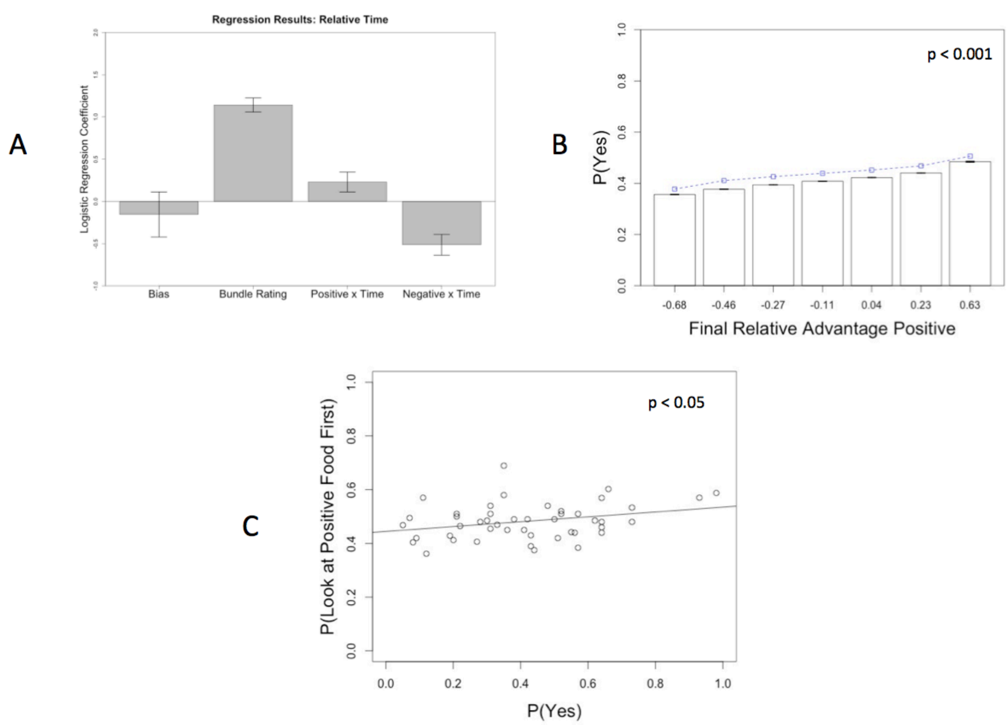


**Figure 6**

Choice Biases. (A) Coefficients from a mixed-model logistic regression of a binary choice outcome (yes or no) on an intercept, rating of the bundle, relative time spent attending to the positive item interacted with the positive item's rating, and relative time spent attending to the negative item interacted with the negative item's rating. (B) Probability of agreeing to eat the bundle as a function of the relative time advantage to looking at the positive item. Bins depict the odd-numbered trials, and the blue dotted line is the model simulation. To compute the bins, the data was split into seven equal bins and the median of each is reported on the horizontal axis. Standard errors clustered by subject. (C) Probability of looking at the positive item first as a function of the probability of agreeing to consume the bundle. Each circle represents a different subject.



**Appendix**

In this section, we list the foods used as experimental stimuli. The precise stimuli used can be downloaded from http://www.rnl.caltech.edu/resources/index.html.

Previously rated appetitive foods from Plassmann et al. (2007):

3 Musketeers Candy Bar
Flamin' Hot Cheetos
Almond Joy Candy Bar
MilkyWay Candy Bar
KitKat Candy Bar
Crunch Bar
Reese's Peanut Butter Cups
Oreos
Tootsie Rolls
Doritos Cool Ranch Chips
Handi-Snacks Chocolate Pudding
Twix Candy Bar
Snickers Candy Bar
Butterfinger Candy bar
Ghirardelli Milk Chocolate
Nature Valley Oats 'N Honey Granola Bar
Milano Cookies
Peanut M&M's

Previously rated aversive foods from Plassmann et al. (2010):

Canned Garbanzo Beans
Pureed Green Beans (baby food)
Canned White Meat Chicken Spread
Soy Sauce
Canned Albacore Tuna
Canned Artichoke Hearts
Pureed Carrots (baby food)
Canned Vienna Sausage
Canned Sweet Peas
Canned Deviled Ham Spread
Canned Sardines
Canned Spinach