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A multiattribute attentional drift diffusion model

Geoffrey Fisher

Cornell University, 340C Warren Hall, Ithaca, NY 14853, United States

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ABSTRACT

Although individuals frequently face decisions over multiattribute outcomes, it is unclear how attentional patterns to the attributes and options of a choice set impact decisions. For example, are unfixated choice options and attributes discounted compared to the currently fixated feature? This paper proposes a model that describes how fluctuations in attention to choice set features impacts decision-making. We test and find evidence for the model's predictions across two laboratory studies where participants made incentivized choices between consuming multiattribute bundles as their eye movements were recorded. The first study finds that an attentional drift diffusion model accurately describes choices, response times, and how these variables are correlated with visual attention to attributes and options. On average, only 80% of an unattended attribute's value and 60% of an unattended option's value were integrated in the evidence accumulation process. The second study exogenously manipulated attention to features of the choice set and found this altered choices, as the model predicts. The attentional bias identified here causally affects decisions and has implications for understanding multiattribute choice.

1. Introduction

The vast majority of decisions individuals make on a daily basis are over multiattribute options. Common examples include dietary choice (e.g., compare options along health and taste attributes), purchasing decisions (e.g., compare goods over quality and price attributes), and decisions over time (e.g., compare options along their monetary amount and delay attributes). Given their prevalence, developing and testing theories of how individuals make these choices is a key interest across multiple fields (Busemeyer & Johnson, 2004; Glimcher & Fehr, 2014; Hastie, 2001; Oppenheimer & Kelso, 2015).

Although it is intuitive that the relative values of attributes and their importance influence choice, the extent to which fluctuations in attention to features of the choice set alters decisions has not been resolved. For example, suppose an individual must choose between ordering two meals at different prices. Furthermore, suppose the first option contains food the individual enjoys more than the second option, but the first is more expensive than the second. As the decision-maker selects an option, their attention will naturally fluctuate between features of the choice set. Is the probability that the consumer chooses a particular option influenced by variables that change the amount of attention deployed to specific features (e.g., the presentation of a menu)? Are there models that can quantitatively explain such effects? Accurate decision-making often requires properly estimating and weighting attributes which can be hampered when there is an effect of attention on choice.

This paper details two studies designed to test the underlying computational process for how attention to options and attributes in multiattribute choice influences decisions. The first study modifies and tests a multiattribute sequential sampling model that tracks attention, as measured by eye gaze. The second study finds that an exogenous manipulation of attention to features of the choice set influences decisions, which provides evidence for a causal role of attention in multiattribute choice.

Previous work suggests sequential sampling models provide quantitatively accurate algorithmic descriptions of the choice process. Prominent examples include the drift diffusion model (Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & Smith, 2004), decision field theory (Busemeyer & Diederich, 2002; Busemeyer & Townsend, 1992, 1993; Diederich, 1997; Roe et al., 2001), and the leaky-accumulator model (Usher & McClelland, 2001). Although there are differences between these models in terms of the contexts they explain and the methods they use, each assumes that individuals make choices by computing a relative decision value signal that evolves over time while combining noisy estimates of choice feature desirability (Mullett & Stewart, 2016). Furthermore, an individual makes a choice once the accumulated evidence reaches a threshold. A sizeable literature has found that sequential sampling models are biologically plausible, and that the brain may utilize similar

E-mail address: gwf25@cornell.edu.

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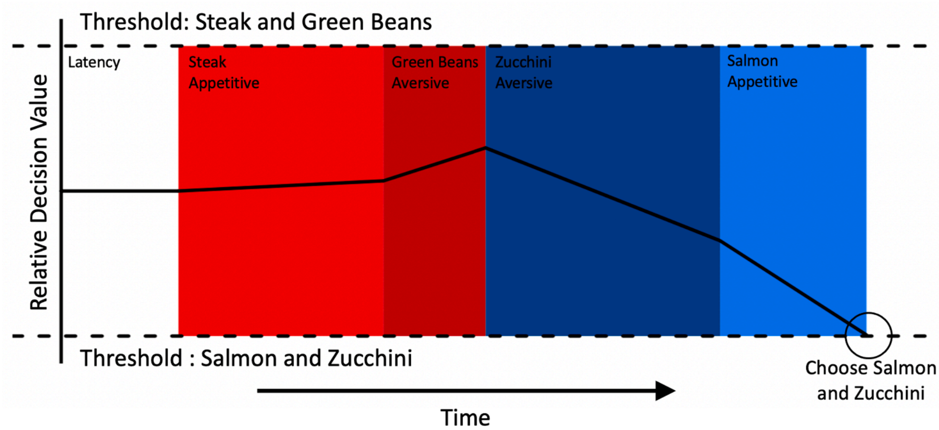

Fig. 1. Visual depiction of the maDDM. A relative decision value (RDV) signal evolves over time. Its slope is biased towards the currently fixated alternative, but the degree of bias depends on the fixated attribute. The shaded vertical regions depict the feature that is currently fixated. A choice is made once the RDV reaches one of the two thresholds. In this example, after a brief latency period where no feature was fixated, four fixations are made (steak appetitive, green beans aversive, zucchini aversive, salmon appetitive) and the individual chose "salmon and zucchini." For simplicity, noise in the evolution of the RDV is not depicted. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

processes when making decisions (Britten et al., 1992; Gold & Shadlen, 2007; Hare et al., 2011; Heekeren et al., 2004; Rangel & Clithero, 2013).

Traditionally, most sequential sampling models have assumed that evidence accumulation is constant throughout a decision. However, recent work has proposed that instead of integrating all possible information into a single evidence stream, processing stages could be differentially represented. This work has allowed for a drift rate in the drift diffusion model that is permitted to vary (Ratcliff, 1980), distinct processing systems that affect preference at different times in the decision-making process (Diederich and Oswald, 2016), and an evidence accumulation rate that depends on the feature that is visually attended to at each moment (Krajbich & Rangel, 2011; Krajbich et al., 2010, 2012; Fisher, 2017; Tavares et al., 2017; Krajbich, 2019). This last point complements a substantial literature that has used process tracing methods (e.g., eye tracking or computer mouse tracking) to understand how attention is allocated during decision-making (Holmqvist et al., 2011; Orquin & Mueller Loose, 2013).

Fig. 1 offers an example to better understand how the model tested in this paper can detail the relationship between attention, choices, and response times. For example, suppose an individual is making a dietary choice between two alternatives placed in front of them and each alternative consists of an appetitive and aversive feature. Specifically, one might decide whether to order steak (appetitive) with green beans (aversive) or salmon (appetitive) with zucchini (aversive) at a restaurant.[1] Given this, there are four unique features an individual could attend to as they make this decision: the appetitive steak, the aversive green beans, the appetitive salmon, and the aversive zucchini. Fig. 1 depicts how the evidence accumulation process for choosing between these two options, as tracked by the evolution of a relative decision value, is affected by attention to each of the four features. Notably, the speed at which evidence is gained depends on the currently fixated feature. For example, Fig. 1 depicts a scenario in which fixating to the appetitive salmon and aversive zucchini features both accumulate evidence in favor of choosing the salmon with zucchini option, but fixating to the appetitive salmon feature gains evidence at a faster rate, as shown by the slope of the relative decision value signal.

Two features are worth noting about this model. First, whereas the details regarding how the relative decision value slope is calculated are presented later, the ability for differences in evidence accumulation to arise as a function of which feature is currently attended originates as a discounting of the unattended option and attribute. For example, when fixating to the left appetitive feature, only a fraction of the value of the unattended option and the unattended attribute are integrated into the relative decision value. This captures the psychological idea that how one deploys attention allows one to favor the currently attended feature. By fitting the model, one can estimate the extent to which unattended variables are discounted. Note that if unattended features were not discounted, attention would not influence choices and evidence accumulation would be constant, regardless of the fixated feature.

Second, the model makes several assumptions about the fixation process, including that the duration of a fixation is largely unrelated to the value of the feature. For example, whereas fixations to different attributes might have different lengths on average, fixations within the same attribute should not be strongly related to the feature's value. Previous work has frequently supported this assumption in simple binary choice tasks (Krajbich et al., 2010), although some evidence has found a relationship between feature value and dwell time in tasks that often have a small number of newly learned stimuli (Cavanagh et al., 2014; Konovalov & Krajbich, 2016).

There are two main contributions of this work. First, this paper estimates the extent to which attention alters the integration of both choice options and attribute values in a multi-attribute setting. Although previous work has used evidence accumulation models to investigate multiattribute choice (e.g., Roe et al., 2001; Bhatia, 2013; Trueblood et al., 2014; Tsetsos et al., 2012; Usher & McClelland, 2004; Wollschläger & Diederich, 2012), combining these models with eye tracking data and testing whether unattended options and attributes are differentially discounted has not been done. We find only 80% of an unattended attribute's value and 60% of an unattended option's value was integrated in the evidence accumulation process when making a fixation to a feature. Most related to this paper, Fisher (2017) used a combination of eye-tracking and computational modeling to explore an accept-reject decision where participants decided whether or not to consume a pair of foods with two attributes. However, that previous work was only able to examine fixation biases on attributes, not options, because the reference option of consuming nothing was constant and always off-screen (i.e., could not be visually attended to). Although the studies here use a similar task to this previous work, the new task more closely approximates a standard multiattribute choice and allows for the estimation of both option and attribute fixation biases. The results find that both unattended options and attributes are discounted, and the model appears to describe the relationship between attention, choices, and response times fairly well.

Second, this paper uses eye tracking to manipulate fixations to individual features of a multi-attribute choice set in order to determine whether there is a causal relationship from attention to choice. Previous work has found that both goal-directed (Bee et al., 2006; Glaholt et al.,

[1] Note that the above scenario can be viewed as more general than it may initially appear in that it captures the intuition underlying many simple multiattribute choice scenarios. For example, purchasing one of two productsentails receiving a beneficial product (appetitive attribute) by paying a monetary cost (aversive attribute). Additionally, an intertemporal choice often requires one to trade off monetary rewards (appetitive attribute) against delays at which they would be received (aversive attribute).

2010; Meißner et al., 2016; Pieters & Warlop, 1999) and stimulus driven properties (Chandon et al., 2009; Lohse, 1997; Milosavljevic et al., 2012; Sütterlin et al., 2008) of the choice set influence attention, and additional work has implicated or suggested that both processes are simultaneously at work (Ashby et al., 2018; Towal et al., 2013; Ghaffari & Fiedler, 2018). Additional work has found that exogenously varying attention can alter choices (Armel et al., 2008; Shimojo et al., 2003; Ghaffari & Fiedler, 2018; Pärnamets et al., 2015; Fisher, 2021). The work here complements these findings by constructing a computational model that allows attention to influence the rate of evidence accumulation in multiattribute choice, and tests for a causal relationship from attention to choice.

These findings are of additional interest to the decision-making community because this model can explain choice patterns and make predictions that previous models could not. A critical aspect of the model is that it details the relationship between choices and other decision process variables, such as the allocation of attention and response times. In particular, the model makes a number of quantitative predictions regarding how variables are correlated and these predictions can be tested using eye-tracking data. For example, there are several predictions about how the order in which features are attended is associated with choices, including a positive association between the initially attended option and the option that is ultimately chosen. Using the model, one can then estimate the probability that the initially attended option is chosen. This has important applications for managers who decide the spatial location of features as these managers would have a quantitative estimate for how simple design changes impact decisions. Finally, as practitioners are often interested in “nudging” decisions, evidence that multiattribute decisions can be altered through visual attention manipulations may lead to policy shifts in how choice features are presented to individuals.

We test and find evidence for the model’s predictions across two laboratory studies where participants made incentivized choices between consuming multiattribute bundles as their eye movements were recorded. All data can be found at https://osf.io/d2ekr/.

2. Study 1: A multiattribute attentional drift diffusion model

The first study was designed to test whether an attentional drift diffusion model could explain patterns in multiattribute choice. The model represents a linkage between choices, response times, and attention. To test the model, we conducted an experiment where laboratory participants made decisions over two pairs of foods, or bundles, to consume at the end of the experiment as their eye movements were recorded. These were multiattribute decisions as each choice was between two visible options with multiple attributes. The model was fit to a portion of the data and an untouched portion tested the model’s predictions.

2.1. Method

2.1.1. Participants

47 students were recruited to take part in the study and we excluded 13 of these participants from completing it. Eight were excluded due to an inability to properly calibrate the eye tracker (i.e., the eye tracker was unable to properly track a participant’s gaze) and five were excluded due to their choice patterns in the initial behavioral tasks.[2] After these exclusions, 34 participants remained (71%, mean age = 22). We planned to collect at least 30 usable participants before analyzing the data. All participants had normal or corrected-to-normal vision. Participants were paid $5 for attending the experimental session and received an additional $20 after the experiment terminated. All participants reported that they had no food allergies and the study was approved by the local Institutional Review Board. Additionally, all participants consumed snacks at the end of the experiment.

[2] These participants did not express enough variability in the first rating task, as described later, to allow the creation of enough choice sets for the final task.

Table 1

Food	Rating	Food	Rating
KitKat	2.26 (0.96)	Hot Cheetos	0.16 (2.11)
Ghirardelli Milk Chocolate	2.22 (0.86)	Tootsie Rolls	−0.22 (1.87)
Milano Cookies	2.12 (0.85)	Almond Joy	−0.31 (2.12)
Twix	2.07 (1.22)	Garbanzo Beans	−0.40 (1.83)
Crunch	1.78 (1.33)	Sweet Peas	−0.76 (1.96)
Oreos	1.69 (1.21)	Tuna	−1.03 (1.93)
Milky Way	1.49 (1.33)	Artichoke	−1.29 (1.77)
Reese’s Peanut Butter Cups	1.24 (2.06)	Spinach	−1.41 (1.67)
Nature Valley Granola Bar	1.16 (1.56)	Chicken Spread	−1.49 (1.49)
Peanut M&Ms	1.10 (1.63)	Beets	−1.71 (1.64)
3 Musketeers	1.06 (1.54)	Green Beans	−1.87 (1.39)
Snickers	1.04 (1.79)	Spam	−1.87 (1.87)
Doritos	0.90 (1.84)	Sardines	−1.97 (1.64)
Vienna Sausage	0.90 (2.08)	Pureed Carrots	−2.07 (1.24)
Chocolate Pudding	0.69 (1.93)	Ham Spread	−2.12 (1.33)
Butterfinger	0.21 (2.07)		

Note: Stimuli used in Study 1. Each stimulus contains the mean rating across participants with standard deviations below in parentheses.

2.1.2. Task

Participants were instructed to fast for four hours before the task. Before taking part in the experiment, participants were asked to report the last time they ate. A participant was only allowed to take the experiment if they reported a time greater than or equal to four hours before the start of the session.

All participants completed three related tasks involving 31 food stimuli. These food stimuli were chosen from previous studies to contain a mixture of appetitive and aversive foods (Plassmann et al., 2007, 2010). Participants were informed at the beginning of the experiment that there would be three tasks, but were only given the instructions for each task immediately before it began. These tasks were modeled partially after those in Fisher (2017).

In the first task, participants entered liking ratings over each individual food item. Each item was shown individually at the center of a computer screen. The image size for each food item was 300 × 300 pixels and the screen resolution was 1920 × 1080. Participants entered a liking rating for each food using a seven-point integer scale (-3 to 3, “how much would you enjoy that particular food at the end of today’s experiment?”). Participants had not time constraint in which to enter their ratings and did so using the bottom row of their keyboard. Each of the 31 foods were displayed twice to each participant in a random order. These ratings were highly correlated over their two presentations (mean correlation = 0.93, SD = 0.07).

Next, the two ratings for each participant and snack were averaged so that participant-specific food categories were created. Foods with a mean positive rating were labeled as “appetitive” and foods with a mean negative rating were labeled as “aversive.” Food items that had a zero-average rating or that received differently signed ratings in their two

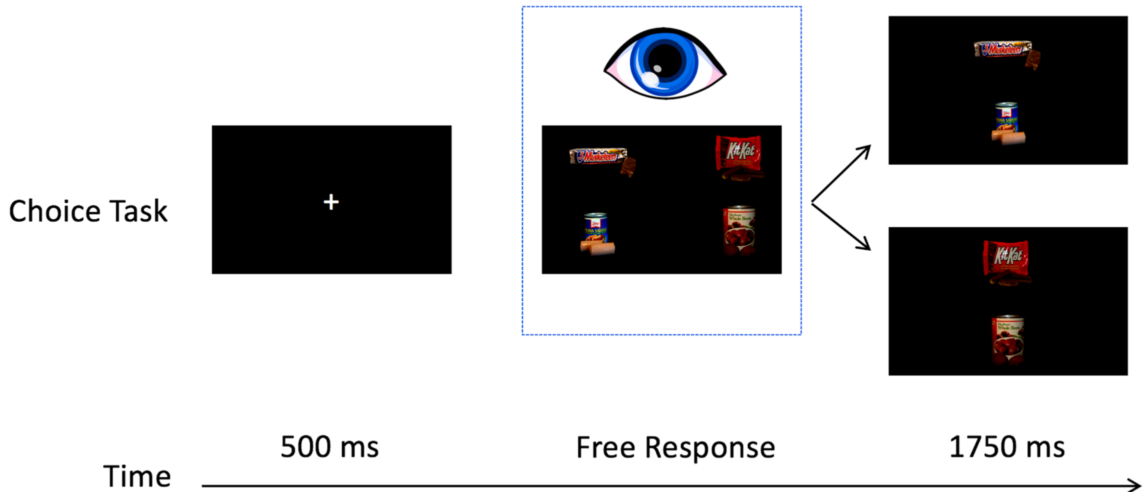

Fig. 2. Experimental design for the choice task. Participants made decisions over whether they would prefer to consume the bundle of foods on the left or the bundle of foods on the right. Each bundle contained an appetitive food and an aversive food. As participants made decisions their eye movements were recorded. The associated timing of each screen is depicted at the bottom of the figure. Each participant saw a fixation cross that had to be fixated to for 500 ms, then had as long as they liked to make a choice. Finally, feedback was displayed for 1.75 s before the next trial commenced.

appearances were not included in the remaining tasks. On average, participants viewed 16 appetitive foods and 15 aversive foods, as described in Table 1.

In the second task, participants rated all possible combinations of bundles of foods, where each bundle contained exactly one appetitive and one aversive stimulus. In this task, participants rated "how much would you enjoy taking at least three bites from both of the foods shown on the screen." One food was shown on the left-hand side of the screen and the other food was shown on the right-hand side of the screen. The location of the appetitive food was randomized across trials. The number of trials in this task varied over participants as it depended on the number of appetitive and aversive snacks (mean = 195, SD = 34). As in the first task, ratings were submitted with the keyboard and participants were not time constrained when entering their ratings.

In the third task, participants made binary choices over pairs of food bundles (Fig. 2). In every trial, participants were shown two bundles from Rating Task 2 and asked to decide which bundle they were willing to consume at least three bites from both of the snacks at the end of the experiment. The location of the appetitive component of each bundle was randomized as either being located at the top or bottom of the screen in each trial, but was the same for both the left and right options in each trial. The choice task was composed of 300 trials which were chosen from all possible bundle combinations. After responding in all trials, one trial was randomly selected and the participant's choice from that trial was implemented. This encouraged incentive compatible responses as participants consumed at least three bites from each item of their chosen bundles.

After consuming their chosen bundle, participants were asked to complete a brief questionnaire. This questionnaire collected demographic information as well as beliefs about the experiment.

2.1.3. Eye tracking

To track the role of visual attention to the options and attributes in the choice task, we used a desktop mounted SR Research Eyelink 1000 Plus to record fixations. The eye tracker recorded at 1000 Hz and was calibrated immediately before participants began the choice task. We used a 13-point calibration exercise to ensure an accurate initial calibration. After every 50 trials, participants were informed how many trials in the choice task they had completed and took part in a calibration drift check to ensure their calibration had not severely degraded over the course of the experiment. All participants passed such a drift check at each prompting.

Fixation location and duration was determined using the SR Research Eyelink software. In order to determine whether a fixation was located on a food image, we defined a region of interest (ROI) around each food image by selecting the 300 × 300-pixel image and adding an additional 75 pixels in all directions that surrounded the image. This procedure attempted to account for measurement noise throughout the choice task. Any fixation inside this ROI is treated as if it were a fixation to the food image.

2.2. Results

2.2.1. Model

This study was designed to test an attentional drift diffusion model's ability to account for the relationship between choices, response times, and how these variables were correlated with fixations in this simple multiattribute choice environment. To see why, here we describe the model and its main properties.

The model assumes that individuals make decisions by accumulating a relative decision value (RDV) signal over time. Once enough evidence is gained in favor of the left or right-side option, a choice is made. Specifically, the participant chooses "left" if a threshold is crossed at B = +1 and chooses "right" if a threshold is crossed at B = -1. Since choice time is equal to the time elapsed until the threshold is crossed, the model also makes predictions about response times.

Importantly, the feature values of the choice set and how attention is deployed can impact the evolution of the RDV, and hence affect choices and response times. The model allows for a fixation bias so that the unattended option and attribute are discounted. Specifically, the RDV's evolution depends on the currently fixated attribute as described below:

$$RDV_t = RDV_{t-1} + d\mu + \varepsilon_t$$

where RDV_t indicates the value of the RDV signal at time t, d is a constant that describes the accumulation speed, ε_t is a draw from $N(0, \sigma^2)$ and reflects the stochastic nature of the process, and μ is equal to:

$$\mu = \begin{cases} (P_L + \delta N_L) - \theta(P_R + \delta N_R), \text{fixation to } P_L \\ (\delta P_L + N_L) - \theta(\delta P_R + N_R), \text{fixation to } N_L \\ -((P_R + \delta N_R) - \theta(P_L + \delta N_L)), \text{fixation to } P_R \\ -((\delta P_R + N_R) - \theta(\delta P_L + N_L)), \text{fixation to } N_R \end{cases}$$

where P_i and N_i refer to the values of the appetitive and aversive foods, respectively, on the ith side of the screen where $i \in \{\text{left}, \text{ right}\backslash\}$, θ and

δ are constants between 0 and 1 that reflect the extent to which the unfixated option and attribute, respectively, are discounted, and "fixation to" represents the location of the currently fixated feature. The psychological intuition for the range of values that θ and δ are permitted to take is that when an option or attribute is out of sight (i.e., unfixated) it is allowed to be, at least partially, out of mind. In this sense, the decision-maker may not account for the true value of an unattended feature but only integrate it partially into the decision process.

The model assumes that a choice option's value is additive and does not contain an interaction term (i.e., a choice option's value does not depend on an interaction of the two attributes). In this sense, the value of an option is relatively simple to compute and this additive structure is consistent with previous multiattribute decision rules that have used linear structures (e.g., Dawes & Corrigan, 1974; Huber, 1979; Keeney & Raiffa, 1993). To test this assumption, we first estimated a linear regression where we regressed the value of the bundle given in the second task on the value of the appetitive and aversive snacks from the first task, separately for each participant.[3] We found the value of the bundle depended on both the appetitive and aversive feature (mean intercept = -2.84, SD = 1.13; mean appetitive slope = 0.45, SD = 0.42; mean aversive slope = 1.13, SD = 0.64, mean R^2 = 0.31, SD = 0.19). To test for an interaction effect, we included an appetitive and aversive value interaction in the above regression. We found the slope on this interaction was 0.09 (SD = 0.32), so it was not significantly different from zero, on average ($t(33) = 1.65$, $p = 0.109$). Additionally, the mean change in R^2 after adding this term was only 0.005 (SD = 0.009). Together, these results suggest that the additivity assumption, without an interaction term, holds in the data.

Additionally, the model makes important assumptions about the fixation process in that the duration of a fixation is largely independent of a feature's value. This means that although fixations to different attributes might have different durations, perhaps due to different processing latencies, fixations within the same attribute should not be strongly affected by the feature's value. For example, fixation duration to an aversive stimulus may last longer than an appetitive stimulus, but within the aversive stimulus the value will not influence fixations. Specifically, the first fixation is to the upper left attribute with probability p_{UL}, upper right attribute with probability p_{UR}, lower left attribute with probability p_{LL}, and lower right attribute with probability $1 - p_{UL} - p_{UR} - p_{LL}$. Fixations are then made between the four features until a threshold is reached. At the start of each fixation, a maximum duration of the fixation is drawn from an empirical fixation distribution that depends both the attribute type (i.e., appetitive or aversive), and whether the fixation is a first or a non-final fixation. The fixation may then reach its randomly drawn duration unless a threshold is achieved before the fixation terminates, which would end the choice process. The below analysis tests these various assumptions.

Several properties of the model should be specifically noted. First, the model includes a "standard" DDM without a fixation bias as a special case, which arises when $\theta = \delta = 1$. Note that in this case, unfixated options and attributes are not discounted. Due to the computational difficulty in fitting large numbers of free parameters in these types of models that integrate physiological data, the model here does not include variability in the starting point, which is assumed unbiased, or the drift rate. However, the model does allow for variance in non-decision time as estimated by a latency until the first fixation.

Second, there is a fixation bias in the model when either $\theta < 1$ or $\delta < 1$. When $\theta < 1$, an exogenous increase in attention to the left (right) bundle biases the decision maker in favor of choosing the left (right) bundle; when $\delta < 1$ an exogenous increase in attention to one attribute biases the decision maker in favor of choosing the bundle that dominates in that attribute.

To see why, consider a decision with choice feature values $P_L = 2$, $P_R = 3$, $N_L = 2.5$, $N_R = 1.5$. First, suppose that there is no attentional bias, i.e. $\theta = \delta = 1$. In such a case, the RDV has a slope of zero and the outcome of random noise determines the choice. Next, suppose there is an option-based attentional bias but not an attribute-based bias, i.e. $\theta < 1$ but $\delta = 1$. Note this model captures the aDDM (Krajbich et al. 2010). Given this, the slope of the RDV is positive when fixating to either attribute of the left bundle, and negative otherwise. Hence, the probability of choosing left depends on the amount of time one fixates to each bundle. Finally, suppose there is an attribute-based attentional bias but not an option-based bias, i.e. $\theta = 1$ but $\delta < 1$. In such a case, the RDV has a negative slope when fixating to the appetitive attribute and a positive slope when fixating to the aversive attribute. Hence, the probability of choosing left depends on the amount of time one fixates to each attribute. When both $\theta < 1$ and $\delta < 1$, the model exhibits different slopes for the RDV depending on which of the four features is fixated. Given this, the model allows for an asymmetric bias in how attention to attributes versus options impacts the evolution of the RDV.

Finally, fitting the model involves estimating four free parameters, $\{d, \sigma, \theta, \delta\}$. An additional parameter of the model is the threshold's separation, which is fixed at the values +/-1. Note that holding the threshold' height constant comes without a loss of generality since multiplying the thresholds, slope, and noise parameters by a constant does not alter the data generated by the model (Ratcliff et al., 2016).

Table 2

d	σ	θ	δ	LL	AIC	p
0.004	0.075	0.6	0.8	−29,363	58,733	–
0.003	0.075	1	1	−29,692	59,387	< 0.001
0.004	0.075	0	0	−29,691	59,387	< 0.001
0.004	0.075	0.6	1	−29,380	58,766	< 0.001
0.003	0.075	1	0.9	−29,691	59,389	< 0.001

Note: Best fitting model parameters and fit statistics. The first row reports the parameters for the best fitting unrestricted model. The following rows report the best fitting no fixation bias model, full fixation bias model, only option fixation bias model, and only attribute fixation bias model, respectively. LL denotes the log-likelihood and p reports the p-value on a likelihood ratio test from a chi-square test of nested models.

2.2.2. Model fit

The model's four free parameters were fit via maximum likelihood estimation on the pooled group data.[4] We pooled all even numbered trials together and estimated group level parameters for this half of the data. Appendix A provides additional details the fitting procedure. In later sections, we compare how well model estimates fit the untouched odd numbered data.

The parameter vector that had the best fit was $(d, \sigma, \theta, \delta) = (004, .075, 0.6, 0.8)$ which had a log-likelihood of −29,363. Table 2 reports model fit statistics for the best fitting no fixation bias model (i.e., $\theta = \delta = 1$), full fixation bias model (i.e., $\theta = \delta = 0$), option only fixation bias model (i.e., $\theta < 1$ and $\delta = 1$), and attribute only fixation bias model (i.e., $\theta = 1$ and $\delta < 1$). For each of these four alternative restricted models, evidence in favor of the unrestricted model was given by a likelihood ratio test ($p < 0.001$ for all four tests). Furthermore, unrestricted model's AIC was lower than each of the restricted models' AIC, suggesting the

[3] In this and all future analyses, we rescale the value of the aversive attribute to a positive number by adding 3.5 to each value. We chose to add this number as this is the maximum number one must add to ensure all aversive stimuli have positive values. Recall the lowest rating for stimuli could be −3. This is done to simplify the interpretation of coefficients and preserves the ordinal relationship of the ratings such that higher ratings are more desirable within an attribute.

[4] When preprocessing the data, we removed trials that had a response time outside of +/- 2 standard deviations from each participant's average response time (mean = 5.0% of all trials, SD = 1.6%). We do this to reduce the noise inherent in the data, although including these trials does not sizably alter the results that follow.

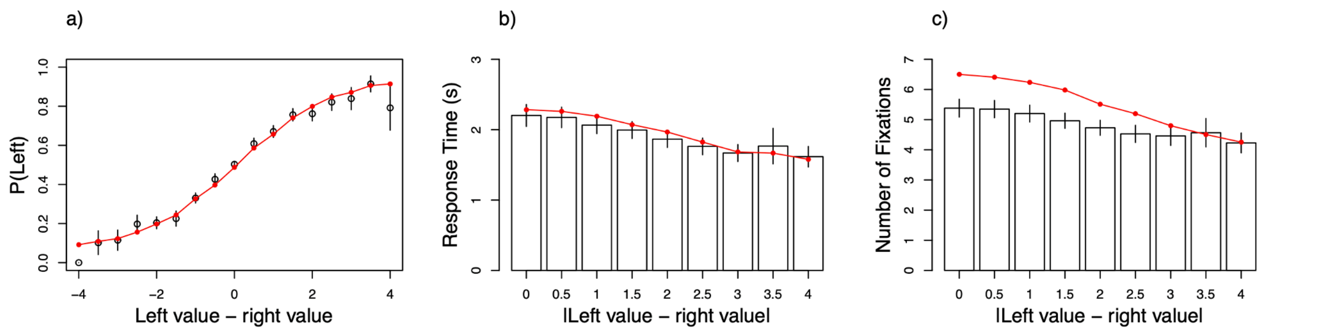

Fig. 3. Psychometrics. a) Psychometric choice curve as a function of the value difference between consumption bundles. b) Response times as a function of a trial's difficulty. c) The number of fixations in a trial as a function of difficulty. Red lines indicate the model's predictions and participant data is shown for the odd-numbered trials, with standard errors clustered by participant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

unrestricted provided a better fit.

In contrast to fitting the model to the pooled data across all participants, Appendix B also reports an estimation technique and results for individual level parameters (see Appendix Table 1). At the individual level we observe variance in estimates across participants. For example, although the presence of a fixation bias is not universal for all participants (θ: mean = 0.54, SD = 0.27, max = 0.9, min = 0; δ: mean = 0.69, SD = 0.33, max = 1, min = 0) these biases do occur for the vast majority of participants. Notably, all participants had a fixation bias on the unattended option and 74% had a fixation bias on the unattended attribute (Appendix Fig. 1). Moreover, the average of each parameter over all participants is close to the group model fit estimates.

Although the above model fit results suggest a model with a partial fixation bias on the attribute and option parameters fits better than various restricted models, the analysis that begins in the next section concerns how well the best fitting model can describe various choice process properties.

In order to generate model predictions, we simulated a data set using the odd-numbered trial parameters (feature values, fixation durations, latencies, etc.) as follows. The model was simulated 5000 times for each possible combination of value rating differences between the left and right bundles, which ranged from -4 to $+4$ by half unit intervals.[5] For every simulation, the liking ratings for the appetitive and aversive items within both the left and right-side bundles were drawn from the empirical distribution of liking ratings conditional on the difference between the sum of the left and right-side bundles.

Additionally, we sampled fixation durations from the empirical distribution of observed pooled group fixations conditional on whether the fixation was a first or middle fixation and whether the attended attribute was appetitive or aversive. We assumed that participant's initial fixations were driven by the spatial location of the four features and that they first looked to each according to the probability observed in the data. Likewise, the saccade process was simulated by using the observed probability of making a saccade from a currently fixated feature to a different feature, conditional on the feature's spatial arrangement and that the current fixation was not a final fixation.

Finally, latencies until a first fixation and saccade time between feature fixations were sampled from the observed distribution. The sum of latencies, feature fixations, and saccade time between feature fixations represents a simulated response time.

2.2.3. *Psychometrics*

Fig. 3 depicts properties of the odd-numbered data compared to the simulated data from the best fitting model parameters that were simulated over the trial parameters of the odd-numbered data. Predictions were made as described in the previous section. In this figure, as well as additional figures, the data is shown in black and the out of sample predictions are in red. The comparison between the odd-numbered data and the simulated data ensures the comparison is an out-of-sample test.

The psychometric choice curve depicts that the probability of choosing the left-hand bundle is a logistic function of the value difference between the left and right bundles (Fig. 3a; mixed-effects logistic regression: constant = 0.022, $p = 0.542$; slope = 0.774, $p < 0.001$). As is common in tests of sequential sampling models, response time was

Table 3

Percent of First Fixations to Each ROI

	Left	Right	
Up	57.1 (28.8)	26.6 (23.5)	83.7 (18.4)
Down	10.8 (14.0)	5.5 (7.1)	16.3 (18.4)
	67.9 (26.2)	32.1 (26.2)	

Note: Percent of first fixations to each ROI. The mean percent of first fixations that were made to each region of interest, given the spatial orientation of the screen. Columns are horizontal orientation and rows are vertical orientation. Means are taken over participant-specific means, and standard deviations are reported below in parentheses.

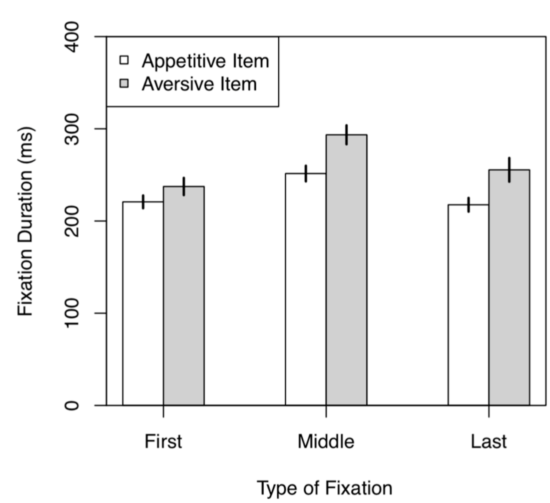

Fig. 4. Fixation durations. The mean fixation duration for first, middle, and last fixations to appetitive and aversive snacks. Standard errors were computed by taking a mean for each participant and then averaging over all participants.

[5] Note that although the difference in left and right values can range from -5 to $+5$, relatively few trials fall outside an absolute difference of 4. To reduce the noise at the extremes of this range, we restrict our analysis to only the trials with an absolute difference of 4.

Table 4

	First		Middle	
Constant	248.1**	256.5**	320.1**	321.5**
	(9.3)	(11.2)	(11.5)	(13.0)
Appetitive Indicator	−13.2**	−13.2**	-32.4**	-33.5**
	(3.8)	(4.2)	(6.3)	(6.5)
Attended Feature	−7.2**	−6.8**	−18.1**	−18.0**
	(2.1)	(2.3)	(3.1)	(3.1)
Unattended Feature A_DO_S		−1.0		2.1
		(2.1)		(2.5)
Unattended Feature A_SO_D		−3.1		0.0
		(2.5)		(2.3)
Unattended Feature A_DO_D		−1.5		−2.9
		(1.9)		(2.6)

Note: Effect of feature values on fixation durations. Linear mixed-effects regressions are reported where fixation duration is regressed on a constant, indicator for whether the currently fixated item is appetitive, the value of the attended feature, and the value of the three unattended features. The notation A_iO_j refers to whether the attribute, A, and option, O, are the same as the attended feature (i.e., i or j equals S) or different from the attended feature (i.e., i or j equals D).

Table 5

	First	Middle
Constant	239.1**	305.3**
	(8.7)	(9.8)
Appetitive Indicator	−17.5**	−44.5**
	(3.5)	(5.7)
|Left Value – Right Value|	−1.3	−8.5**
	(1.6)	(2.2)

Note: Effect of choice ease on fixation durations. Linear mixed-effects regressions are reported where fixation duration is regressed on a constant, indicator for whether the currently fixated item is appetitive, a measurement of choice ease.

correlated with difficulty (mixed-effects linear regression: slope = -0.169, $p < 0.001$), where difficulty was measured by the absolute value of the difference between the sum of left and right liking ratings (see Fig. 3b). Appendix Fig. 2 plots the observed versus predicted response time for each type of trial based on the difference in liking ratings and finds a strong association between the two. Finally, the number of fixations increased as difficulty increased (mixed-effects linear regression: slope = -0.318, $p < 0.001$), consistent with the relationship between response time and difficulty (see Fig. 3c). As can be seen in the figure, the model's predictions closely match the observed out-of-sample data. On average, participants made 5.1 fixations (SD = 1.4) per trial.

Fig. 3 is reproduced for each participant using the individual model fits from Appendix Table 1 and given is shown in the Online Appendix. Overall, the model appears to capture the psychometric patterns although, as expected given the smaller individual sample size, the results are noisier compared to the aggregate fit.

2.2.4. Properties of the fixation process

Here, we describe the fixation process that participants engage in and whether it is consistent with the model's assumptions.

The location of participants' first fixation is shown in Table 3. Participants were likely to first look to the upper left region of interest, and were more likely to first look up ($t(33) = 10.71$, $p < 0.001$) and first look to a left attribute ($t(33) = 15.14$, $p < 0.001$). There was no bias to first looking at the aversive attribute (mean = 51.7%, SD = 4.5%) which indicates participants did not initially notice color other low-level saliency differences between appetitive and aversive foods as the location of the attributes were randomized across trials ($t(33) = 1.67$, $p = 0.105$). Additionally, participants were not more likely to make an initial fixation to the more preferred bundle ($t(33) = 1.74$, $p = 0.091$) indicating that they could not identify preferred choice options based on saliency features. Together, these results suggest that the location of initial fixations are largely driven by the spatial location of stimuli and not the value of choice set features.

As depicted in Fig. 4, fixations that were made to aversive features were approximately 35 ms longer than those to appetitive features for all fixation orderings (first: $t(33) = 4.07$, $p < 0.001$; middle: $t(33) = 6.57$, $p < 0.001$; last: $t(33) = 4.63$, $p < 0.001$). This finding is consistent with the model's assumptions described above in that fixations to different types of attributes can follow different processes. Here, that process is that the aversive attribute has a longer processing latency than the appetitive attribute.

We next tested whether the value of the choice features altered fixation durations. Table 4 reports the results of an analysis where fixation duration is regressed on a constant, indicator variable for whether the currently fixated feature is appetitive or aversive, and the value of the currently attended feature for both first and middle fixations. We add the attribute indicator to the regression, as the above results found fixation duration was increased for fixations to aversive features. Additional analyses controlling for the value of the three unfixated features are also reported. For both the first and middle fixations, the attended feature's value was negatively correlated with fixation duration, although the point estimates suggest the effect is relatively small in all cases. For instance, a change from a feature's minimum possible value to its maximum was associated with an initial fixation difference of only 17 to 18 ms. Moreover, the value of all the unattended features were not associated with differences in fixation duration. Finally, Table 5 reports a similar analysis with choice difficulty as an independent variable and finds that the first fixation was not impacted by the difficulty of the choice, but the duration of the middle fixation was to a small degree. However, a shift from the easiest to most difficult decision was only associated with a middle fixation difference of 34 ms. Overall, these results suggest that the value of the choice set features do not play a strong role in determining the fixation duration.

Finally, we examine the factors that influence the direction of the next saccade in the fixation process. Table 6 reports the mean probability of making a fixation to an ROI conditional on the location of the current fixation. Regardless of the location of the current fixation, the next saccade was likely to be either within-attribute (i.e., horizontal) or within-option (i.e., vertical). Overall, 39.4% (SD = 6.8%) of saccades were within-attribute, 50.0% (SD = 5.2%) were within-option, and only 10.6% (SD = 3.5%) were between attribute and option (i.e., diagonal). Given this, individuals were overall more likely to make within-option compared to within-attribute saccades ($t(33) = 5.35$, $p < 0.001$), although there was heterogeneity in this measure (mean = 10.7%, SD = 11.6%, max = 33.8%, min = -17.7%).[6] Appendix C reports the results of several additional analyses that investigate the heterogeneity of the individual estimated model parameters as they relate to fixation strategies. For the most part, there are few results that suggest different fixation patterns are associated with particular model estimates (Table 7).

Given the relatively small number of diagonal fixations, we next examine how the value of the features impacted the likelihood of making a within-option saccade (i.e., vertical) as opposed to a within-attribute saccade (i.e., horizontal). To do this, we ran a mixed-effects logistic regression where we regressed a binary variable for whether a

[6] A total of 26 of the 34 participants (76%) in the study were more likely to make a within-option saccade than a within-attribute saccade. Noguchi & Stewart (2014) found the opposite result in their data, namely that within-attribute saccades were more prominent than within-option saccades. However, their results may not be directly comparable to the context here as they studied choices with more than two options. Furthermore, it is possible that the propensity to make a certain type of saccade is driven by the location of features on the computer screen which differed between studies.

Table 6

		To:		
		Same Option	Same Attribute	Other
From:	Upper Left	0.49	0.44	0.06
	Upper Right	0.56	0.34	0.09
	Lower Left	0.46	0.39	0.15
	Lower Right	0.50	0.39	0.11

Note: Saccade patterns. The mean probability of making a fixation to an ROI (columns) conditional on the location of the current fixation (rows).

saccade was within-option (i.e., 1 if within-option and 0 if within-attribute) on the values of the choice set features. Table 6 reports the results. Although the value of the current feature was positively associated with making a within-option saccade, the size of the effect was quantitatively small. To better examine this, we report an effect size estimate in bold below each estimated coefficient. This estimate computes the change in the probability of making a within-option saccade as a dependent variable moves from its highest to lowest value, conditional on all other variables taking their mean value observed in the data. Given this, the maximum possible change in an attended feature's value was only associated with an 11.8% change in the propensity to make a within-option saccade. Additionally, we found a quantitatively small effect of difficulty on saccade direction (slope = 0.07, $p < 0.001$; mean effect size = 6.5%). Like fixation duration, the results here suggest there is only a minor impact of feature value on saccades.

2.2.5. *Model predictions*

The model makes several additional predictions regarding how patterns of fixations are related to choices, and these are tested below.

First, the model makes the prediction that final fixations have a shorter duration than middle fixations. The logic for this is straightforward: final fixations are terminated early as the RDV crosses a threshold before the fixation is terminated by reaching its randomly selected duration which was drawn from the empirical distribution of possible fixations. This finding holds in the data (Fig. 4; mean last = 235 ms, mean middle = 274 ms; $t(33) = 6.39$, $p < 0.001$). Additionally, first fixations were shorter than middle fixations (mean first = 229 ms, mean middle = 274 ms; $t(33) = 6.46$, $p < 0.001$) and this finding was incorporated in the estimation procedure through the separate sampling of first and middle fixations as described above.

Additionally, conditional on the choice an individual makes, the model predicts an association between the fixation-averaged value that is computed at the start of the last fixation and the duration of that last fixation. For instance, given that the individual chose the left-hand option, the final fixation's duration should be negatively correlated with:

$$F_{P_L}((P_L + \delta N_L) - \theta(P_R + \delta N_R)) + F_{N_L}((\delta P_L + N_L) - \theta(\delta P_R + N_R))$$

$$-F_{P_R}((P_R + \delta N_R) - \theta(P_L + \delta N_L)) - F_{N_R}((\delta P_R + N_R) - \theta(\delta P_L + N_L)),$$

where F_{i_j} is the fraction of the trial, before the final fixation, spent attending to the $i \in \{\text{appetitive, aversive}\}$ attribute on the $j \in \{\textit{left}, \textit{right}\}$ of the screen. The intuition underlying this relationship illustrates several important components at work in the model. Conditional on choosing left, the larger the fixation-averaged value before the final fixation, the shorter the final fixation should be as the RDV is already "close" to the left threshold. Likewise, the lower the fixation-averaged value before the final fixation, the more evidence the individual has in favor of choosing the right-hand option, the more distance would need to be covered in order to choose the left option. Hence, the longer the final fixation would be.

This prediction was tested by conducting a mixed-effects regression of the final fixation duration on the final fixation averaged-value, as defined above, conditional on the participant choosing "left." There was a significant effect in the hypothesized direction (slope = -12.41, $t(33) = -2.94$, $p = 0.003$). Furthermore, the model makes a similar prediction for trials in which participants choose "right," although the sign of the effect flips. This effect was also observed in the data (slope = 16.36, $t(33) = 3.80$, $p < 0.001$).

The above results are consistent with the hypothesized relationships between fixations and choices.

2.2.6. *Choice biases*

When $\theta < 1$ and $\delta < 1$, the model makes a number of predictions that the standard DDM, i.e. $\theta = \delta = 1$, does not make. These predictions are tested below and involve a number of correlations between attention and choice.

First, the model predicts that, controlling for the value of the four features, the likelihood of choosing the left option increases with time spent attending to either of the left features, and decreases with time spent attending to the right-hand features. The intuition for this is that additional time spent attending to a feature allows the decision-maker to gain evidence in favor of choosing the option associated with the attended feature. To test this prediction, we ran a logistic mixed-effects regression where a binary variable for choosing the left option was regressed on the feature values and their interaction with fixation time. The signs on the interactions are significant and in the direction predicted by the model (data: either left feature slope = 0.001, either right feature slope = -0.001, $p < 0.001$ for all four slopes; simulation: either left feature slope = 0.001, either right feature slope = -0.001, $p < 0.001$ for all four slopes). Note that the size of each interaction can be quite substantial as an increase of 1 ms duration to a feature is associated with an increase of 0.001 in the log-odds of selecting an option.

Second, the model predicts that the probability of choosing the left bundle depends on the relative amount of time one attends to each of the left-hand features compared to their right-hand features. To test this prediction, we compute a corrected choice measure by subtracting the observed choice (left = 1, no = 0) from the average frequency with which the left option was chosen for all trials with that difference in liking values. In Fig. 5a, we pool the data across attributes within the same option and verify that an increased time advantage to either of the left-hand features is associated with an increased probability in choosing the left-hand option in both the data (slope = 0.0003, $p < 0.001$) and simulated model (slope = 0.0001, $p < 0.001$).

To examine this effect at an attribute level, we then estimated a

Table 7

Constant	−0.03	0.13
	(0.05)	(0.08)
Appetitive Indicator	0.09*	0.15**
	(0.04)	(0.04)
	2.2%	**3.7%**
Attended Feature	0.16**	0.18**
	(0.02)	(0.02)
	11.8%	**12.9%**
Unattended Feature A_DO_S		−0.04
		(0.02)
		−3.2%
Unattended Feature A_SO_D		−0.13
		(0.02)
		−9.4%
Unattended Feature A_DO_D		0.03
		(0.02)
		2.5%

Note: Effect of feature values on saccade patterns. Logistic mixed-effects regression where a binary variable for making a within-option saccade, as opposed to within-attribute, is regressed on an indicator for the current fixation being to an appetitive food, the value of the attended feature, and the value of the three unattended features. The notation A_iO_j refers to whether the attribute, A, and option, O, are the same as the attended feature (i.e., i or j equals S) or different from the attended feature (i.e., i or j equals D). The mean effect size of moving each independent variable throughout its range, holding all other variables at their mean value, on the probability of making a within-option saccade is shown in bold below each estimate and standard error.

linear regression of the corrected choice probabilities on the relative time advantage to the left appetitive and aversive attributes. Both increased attention to the left feature for each of the attributes was correlated with an increased probability of choosing the left-hand option in the data (appetitive slope = 0.0004, $p < 0.001$; aversive slope = 0.0002, $p < 0.001$) and the model (appetitive slope = 0.0001, $p < 0.001$; aversive slope = 0.0001, $p < 0.001$). These results suggest that relative attention differences at an attribute level are associated with choice biases.

Third, any biases in the first attended feature should be correlated with choice biases. Fig. 5b and 5c show this is the case for all four features, and linear regressions verify this for the left appetitive attribute (slope = 0.17, p = 0.016), left aversive attribute (slope = 0.17, p = 0.015), right appetitive attribute (slope = -0.17, p = 0.019), right aversive attribute (slope = -0.16, p = 0.013). The logic underlying this relationship is that an initial fixation to a feature moves the RDV closer to the threshold associated with that feature's option and, hence, increases the probability the option is chosen. Note that a strong impact for earlier attended features is also consistent with previous psychological theories, in particular those from query theory which argue that earlier queries more heavily affect value than later queries (Johnson, Häubl, & Keinan, 2007; Weber et al., 2007).

Finally, the model makes predictions about the relationship between the location of the final fixation and choice. Specifically, the model predicts that, controlling for the difference in ratings, the probability of choosing the left option is larger when the last fixation is to a left attribute. To see why, note that attending to either left attribute is typically associated with a slope of the RDV that is biased towards the left option. Fig. 5d and 5e show this is indeed the case for the appetitive and aversive attributes. To quantitatively test for this effect, we regressed a binary variable for whether or not a participant chose the left-hand option on the difference in liking ratings and an indicator variable for whether the last fixation was to a left feature, separately for the appetitive and aversive attributes. We found a sizeable bias on this indicator term in both regressions for the data (appetitive slope = 1.11, $p < 0.001$; aversive slope = 1.42, $p < 0.001$) and model (appetitive slope = 1.33, $p < 0.001$; aversive slope = 1.30, $p < 0.001$). The biases in the model follow a quantitatively similar pattern to the data. Note that finding a strong impact of the last fixation is consistent with previous work that has found evidence of recency effects in decision-making (Häubl, Dellaert, & Donkers, 2010; Li & Epley, 2009; Wedel & Pieters, 2000).

Overall, the data confirms a number of patterns between choices and fixations that are identified by the model with the estimated option and attribute fixation biases found here. Moreover, the findings are consistent with previous work that has explored how information acquired at different points in the decision process influence choice. Finally, the results here could be used to improve forecasts for how simple shifts in attentional variables (e.g., spatial location of an attribute) influence decisions.

3. Study 2: Causal attentional manipulation

The above study found that the proposed model was able to quantitatively account for the relationships between choices, response time, and how these variables are correlated with attentional patterns in a simple multiattribute choice task. However, the theory predicts a causal relationship between attention and choice and the above evidence is purely correlational. To address this issue, we ran an additional experiment where we manipulated fixation duration to features in order to test for causality.

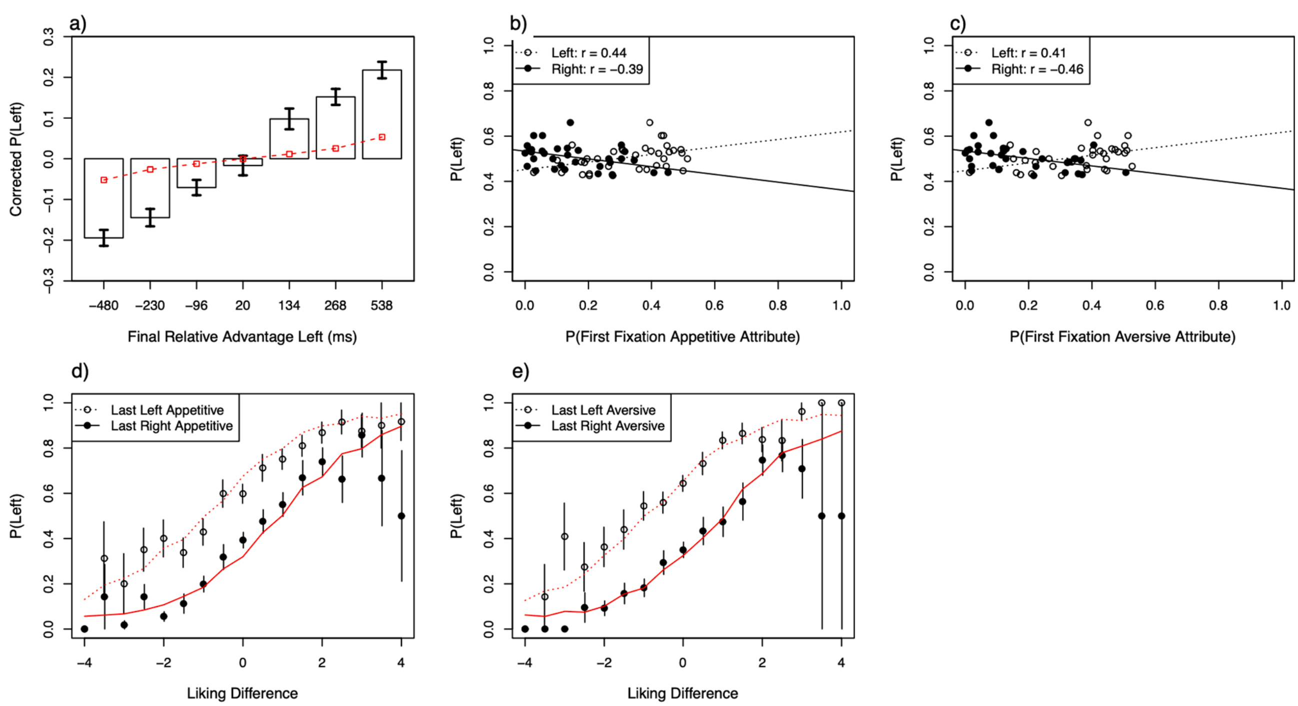

Fig. 5. Choice biases. a) The corrected probability of choosing the left option as a function of the relative time advantage fixating to the left option. Bins display the odd-numbered trial data and the red line is the best fitting model's prediction. In order to compute the bins, the data was grouped into seven equal bins and their medians are reported on the horizontal axis. b) Probability of choosing the left-hand option as a function of first looking at the left appetitive attribute (white circles) or right appetitive attribute (black circles). Each circle depicts a different participant. c) Same as (b) but for the aversive rather than appetitive attribute. d) Probability of choosing the left-hand option as a function of the liking difference between options and whether the last fixation was to the left or right appetitive feature. White and black dots indicate the odd-numbered data when the last fixation was to the left or right appetitive attribute, respectively, and dotted and solid red lines indicate the model predictions when to the left or right appetitive attribute, respectively. Standard errors are clustered by participant and can be large for the extreme values due to a low number of observed trials in those bins. e) Same as (d) but for the aversive rather than appetitive attribute. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.1. Methods

3.1.1. Participants

A total of 50 students were recruited to take part in the experiment. The set of participants recruited for this experiment did not overlap with Study 1. We excluded 17 participants from completing the experiment due to an inability to either properly calibrate the eye tracker or abnormal patterns in the initial behavioral tasks which was identical to Study 1. After these exclusions, which did not generate a full data set across the tasks described below, 33 participants remained (64% female; mean age = 23.6). We planned to collect at least 30 participants before analyzing the data. All participants had normal or corrected-to-normal vision. Participants were paid $5 for attending the experimental session and received an additional $20 after the experiment terminated. All participants reported that they had no food allergies and the study was approved by the local Institutional Review Board.

3.1.2. Task

Participants were asked to fast for four hours prior to the task and compliance was verified through self-report.

Participants completed two related tasks involving 31 food stimuli. They were informed at the beginning of the experiment that there would be two tasks; however, they were only given the instructions for each task immediately before it began.

The first task was identical to the first task from Study 1. Specifically, participants entered a liking rating for each food using an integer scale (-3 to 3, framing: “how much would you enjoy that particular food at the end of today’s experiment?”). Each of the 31 foods were displayed twice to each participant in a random order. As before, we averaged both ratings for each snack and participant in order to create participant-specific “appetitive” and “aversive” classes. On average, participants had 16 appetitive foods and 15 aversive foods and the ratings were qualitatively similar to Study 1 (see Table 8).

Table 8

Food	Rating	Food	Rating
KitKat	2.33 (0.79)	Chocolate Pudding	−0.02 (1.89)
Ghirardelli Milk Chocolate	2.18 (0.74)	Tootsie Rolls	−0.35 (2.18)
Milano Cookies	1.89 (1.30)	Garbanzo Beans	−0.97 (1.71)
Crunch	1.79 (1.23)	Tuna	−1.55 (1.81)
Peanut M&Ms	1.74 (1.08)	Sweet Peas	−1.74 (1.38)
Oreos	1.56 (1.30)	Spinach	−1.88 (1.38)
Reese’s Peanut Butter Cups	1.38 (1.75)	Beets	−1.89 (1.58)
Twix	1.36 (1.84)	Vienna Sausage	−1.97 (1.52)
Snickers	1.20 (1.61)	Pureed Carrots	−2.00 (1.49)
Doritos	0.79 (1.56)	Artichoke	−2.08 (1.35)
Milky Way	0.73 (1.78)	Spam	−2.23 (1.32)
3 Musketeers	0.64 (1.80)	Chicken Spread	−2.32 (1.18)
Hot Cheetos	0.56 (2.06)	Green Beans	−2.36 (0.99)
Nature Valley Granola Bar	0.52 (1.64)	Sardines	−2.45 (1.05)
Butterfinger	0.35 (2.00)	Ham Spread	−2.52 (1.08)
Almond Joy	0.09 (2.12)		

Note: Stimuli used in Study 2. Each stimulus contains the mean rating across participants with standard deviations below in parentheses.

In the second task, participants completed a similar choice task between two bundles, as in Study 1. However, the task here contained a critical difference in that we attempted to exogenously increase attention to one of the four features in a choice set (i.e., either the left appetitive feature, right appetitive feature, left aversive feature, or right aversive feature). Here, participants answered 201 questions between choosing a bundle on the left-hand side of the screen or a bundle on the right-hand side of the screen. A set of 50 questions were each repeated four times to generate 200 questions. In each repetition, we attempted to shift attention exogenously to one of the four features on the screen. Additionally, we generated one question that was identical across participants to facilitate similar consumption options across participants. In the results, we exclude the analysis of this trial since it was not displayed in all four conditions.

We sought to alter attention to each of the four features in the following way. First, we defined one of the four features as the “target.” In each of the four repetitions of each choice set, each of the four features was chosen to be the target feature exactly once. The target feature appeared in isolation on the screen for an amount of time chosen randomly from the interval [500 ms, 850 ms], which was larger than typical fixation time to features from Study 1. Non-target features appeared in isolation on the screen for an amount of time chosen randomly from the interval [200 ms, 260 ms], an amount of time approximately equal to the typical fixation duration from Study 1. This timing was utilized so that participants would be able to accurately perceive all stimuli. Although features were displayed one at a time in isolation from one another, they appeared in spatially distinct locations as in the choice task for Study 1. Specifically, each feature would appear in either the upper left, upper right, bottom left, or bottom right section of the screen. As in Study 1, the location of the appetitive and aversive stimuli were randomized as either being located on the top or bottom of the screen.

Once a feature was fixated at for the predetermined amount of time, as determined by the eye tracker, that feature disappeared from the screen. Next, a different feature was shown in a spatially distinct region until all features had been displayed exactly once. Viewing times were enforced by the eye tracker in that the eye tracker actively recorded the amount of time a participant fixated to each feature and once it was viewed for its predetermined duration, the feature disappeared from the screen. Each feature was displayed exactly once, and the order in which each feature appeared was randomized, both by location and by whether or not the the feature was the target feature. After viewing all features, a question mark was placed in the center of the screen which served as the participant’s prompt to enter their choice to consume the left options (by pressing “v” on the keyboard), or the right options (by pressing “b” on the keyboard).[7] Participants were only able to enter their choice once the question mark appeared.

Previous work suggests that even in short enforced fixation times like those used here, participants are able to recall features that were viewed. Furthermore, the shorter fixation times used here closely match the free fixation viewing patterns from Study 1. Finally, note that as this task was monitored by the eye tracker, participants actually had to fixate on a feature for the predetermined amount of time before that feature was removed from the screen.

After consuming their chosen bundle from the selected trial in the experiment, participants were asked to complete a brief questionnaire. This questionnaire collected demographic information as well as beliefs about the experiment.

[7] In an open-ended question at the end of the study, participants were asked, “what do you think this study is about?” Two participants referenced that we were interested in how order or differential attention to the images influences choices. Removing these participants from the data set does not alter the significance of the results below.

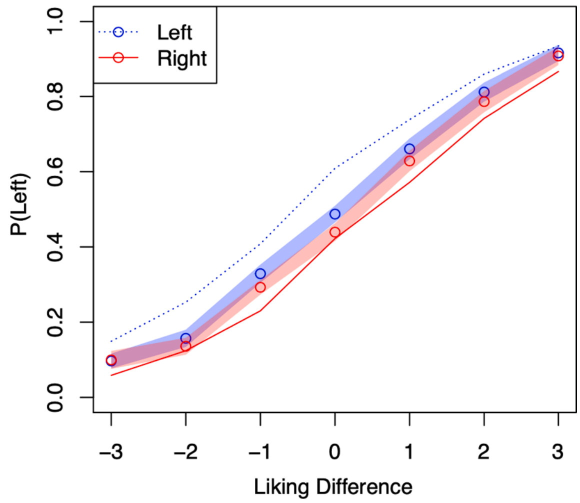

Fig. 6. Study 2 attentional manipulation. The probability of choosing the left option as a function of the liking difference between options. Colored circles represent the data with standard error bars, and lines represent the best fitting model's prediction. Blue indicates the attentional manipulation was on a feature of the left option and red indicates the attentional manipulation was on a feature for the right option. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Results

When the target feature was the left appetitive or left aversive stimulus, participants chose the left outcome 49.2% (SD = 7.5%) and 48.4% (SD = 7.2%) of the time, respectively. However, when the target feature was the right appetitive or right aversive stimulus, participants chose the left outcome only 46.6% (SD = 6.8%) and 46.5% (SD = 7.7%) of the time, respectively. Hence, exogenously shifting fixations to a left vs right feature increased the probability of choosing the left option by 2.3% ($t(32) = 3.50$, $p = 0.001$). Moreover, shifting attention to the left rather than right appetitive attribute increased the likelihood of choosing the left option ($t(32) = 2.81$, $p = 0.008$) and shifting attention to the left rather than right aversive attribute increased the likelihood of choosing the left option ($t(32) = 2.32$, $p = 0.027$).

To explore how well the model fits the data, we used the best fitting model parameters from Study 1 to predict a choice in each trial, given the observed pattern of fixations and feature values. Fig. 6 plots the data and this model prediction dependent on whether the attentional manipulation was towards a feature on the left or right option. The data mimics the model's prediction in that there is a higher likelihood of choosing left when attention is shifted towards a left feature for most liking difference values. However, the effect size is notably smaller than the model predicts.

There are at least three reasons why the observed effect is smaller than the model predicts. First, unlike Study 1 participants fixations are not free to vary but are carefully manipulated to each feature for a predetermined amount of time. It is possible that these changes from natural fixation patterns influence the effectiveness of the manipulation. Second, the manipulation successfully biases fixations, but not necessarily attention throughout the decision process. The reason why is that a choice could have been made before attention was biased to the predetermined feature. Third, it is possible that, despite some of the evidence from Study 1 and previous literature, attention is more endogenous than previously hypothesized. However, despite the smaller than expected size these results are consistent with the existence of a causal path from attention to choice in the multiattribute setting explored in the studies.

4. Discussion

The results here are a step towards better understanding how attention to choice features affects multiattribute decision-making. A modified attentional drift diffusion model was fit to a simple multiattribute choice environment and the predictions of the model were tested in two laboratory experiments that employed eye tracking. Importantly, the model is focused on the process of the decision itself, rather than solely on choice outcome; hence, it makes quantitative and testable predictions about the relationship between choices, response times, and attention to features of the choice set. The results suggest the model can provide an accurate description of the choice process.

Model fitting results and additional tests suggest evidence for a fixation bias in multiattribute choice. Specifically, how value is dynamically integrated changes depending on the currently attended attribute and option. In the model, this change is related to the speed, or drift, of evidence accumulation in favor of either consuming the left or right-hand option. The data suggests that only 80% of an unattended attribute's value and 60% of an unattended option's value was integrated in the evidence accumulation process. This fixation bias has important implications that extend to the observed behavioral phenomena. For instance, the more time spent attending to either left-hand attribute increased the probability of consuming the left-hand bundle. Additionally, participants who looked first at either feature of a bundle were more likely to choose it, even though there is sizeable trial by trial noise as to the feature participants first attended. These, among other findings, demonstrate that eye fixations to attributes and options impact choices in several key ways that the model predicts.

An important question about the model concerns the direction of causality between fixations and choice. Specifically, whereas the model assumes that fixations alter the value comparison process, it is also possible that attribute values influence the fixation process. Indeed, after controlling for the fixated attribute type we find that lower value features are fixated for longer durations, but the size of this effect is relatively small. We address this assumption in the second study where we attempt to vary attention via an exogenous manipulation. We find that, regardless of the attribute, increasing fixation duration to a feature leads to an increased probability of selecting the option that has an increased amount of attention. This relates to previous work that has found fixations bias decision-making which has important practical implications for managers seeking to nudge choices (Armel et al., 2008; Milosavljevic et al., 2012; Ghaffari & Fiedler, 2018; Pärnamets et al., 2015; Fisher, 2021). Additional evidence from neuroscience finds that the ventromedial prefrontal cortex encodes relative value signals that are altered by attention which suggests that fixations may alter the value comparison process (Lim et al., 2011).

Although Fisher (2017) explored a similar choice environment (i.e., accept-reject decisions with an appetitive and aversive stimulus), the contribution here differentiates itself in several important ways. First, the setting here models a more complex multiattribute choice paradigm and thus, can estimate the degree to which participants underweight both unfixated attributes and unfixated options. Of note is that whereas Fisher (2017) found a relatively small attribute fixation bias, the data here finds that 80% of an unattended attribute's value and 60% of an unattended option's value was integrated in the evidence accumulation process. It is possible this difference is due to the nature of the choice task employed: binary as opposed to accept-reject choices. Moreover, the results here suggest that attention to either attribute of a choice option is associated with an increased probability of selecting it, which is consistent with some previous sequential sampling models (e.g., Gossner et al. 2018). This suggests an intriguing relationship between combinations of appetitive and aversive stimuli. Although previous work has found that increased attention to an aversive option is negatively correlated with the propensity to select the attended option in binary choice (Armel et al., 2008) and that attention to an aversive attribute is negatively associated with selecting the associated option over a reference option in accept-reject decision (Fisher, 2017), it is possible that this relationship reverses when choices are multi-attribute and over multiple options, as found here. Future work should investigate how the pattern of evidence accumulation relates to the choice setting and context (e.g., accept-reject versus two-alternative forced choice). Finally, the work here tests the attention causality assumption inherent in previous attentional drift diffusion models and finds it is supported by the data: manipulating attention to features alters choices in ways the model predicts.

Several psychological and practical implications emerge from these results. First, although substantial evidence indicates context variables affect decisions (e.g., Ariely et al., 2003; Tversky & Kahneman, 1974; Johnson & Schkade, 1989; Simonson, 1989; Read & van Leeuwen, 1998), we lack a systematic understanding for how such variables influence choice. The approach here suggests that an important component of this problem is to better understand how context variables influence attention. For example, certain context effects might arise due to changes in attentional allocation and models that integrate attentional data, such as variations of the one here, might be able to more accurately estimate the presence and size of such effects. Relatedly, recent work has found that context effects can increase with deliberation time (Pettibone, 2012; Trueblood et al., 2014) which is consistent with the prediction from certain sequential sampling models.

Second, although the model details a decision environment over appetitive and aversive foods, this structure relates to common managerial problems in organizational settings such as purchasing decisions and intertemporal tradeoffs. For example, note that in each of these additional settings the decision-maker receives a benefit (e.g., product or monetary amount) and experiences a cost (e.g., monetary cost to purchase a product or delay date). The findings here suggest that most individuals do not fully account for unattended features as they make decisions. However, the vast majority of model-based predictions in these settings do not account for such variation in attention. Capturing additional decision process variables, such as attentional deployment, frequently improves predictions and can lead to more accurate forecasts (Stüttgen et al., 2012; Willemsen et al., 2011).

Third, the model predicts that fluctuations in attention can influence choices. That is, attentional manipulations can nudge individuals to select the more attended alternative. This is practically useful in situations where managers may attempt to nudge or retrain attention to influence decisions rather than attempt to alter underlying preference parameters that could be comparatively inflexible. For example, time pressure is a ubiquitous factor found across organizational settings that has been found to influence a wide array of choice domains including intertemporal choice (Lindner & Rose 2017), risky decision-making (Guo et al., 2017; Svenson et al., 1993; Saqib & Chan, 2015), and purchasing decisions (Dhar & Nowlis 1999). In cases where time pressure can induce pervasive effects, managerial tools that manipulate attention might reverse or dampen such effects. Although the model here overpredicted the effect of an exogenous manipulation of attention relative to the data in Study 2, there may be alternative manipulations that more closely match the quantitative predictions.

We conclude by noting three limitations of our work. First, the model assumes that fixations should be independent of a feature's value, yet the data finds evidence of a small correlation in certain analyses. For example, fixation duration was correlated with a feature's value although the size of the effect was found to be small. Additionally, a feature's value could impact the propensity to make a within-option versus within-attribute saccade by up to 12%. Although these findings do violate an assumption of the model, they also indicate that when there is an effect of value on the fixation process in this task, it is often quite small in magnitude. Furthermore, it is worth noting that in many other analyses, the assumptions in the fixation process are justified by the data. Ultimately, future work should attempt to better understand the relationship between value and attention in multiattribute choice.

Second, the environment participants are placed in is fairly artificial as they face a large number of trials 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 for the accurate estimation and testing of the proposed model and is likely correlated with real-world decision-making. Specifically, in order to fit the model a large number of choices must be observed so that precise parameter estimates can be pinned down and tested in an out-of-sample comparison. Although the questions asked of participants here are frequent and over a common set of snacks, many decisions individuals engage in are often repetitive and numerous. Moreover, we are able to better understand how valuations of single attributes are integrated together to determine a consumption value of a multiattribute option, which is a fairly novel task. In future research, it would be useful to apply this style of model to observable real-world choices such as naturalistic multiattribute choice (Bhatia & Stewart, 2018), where process tracking data might also be available. Additionally, it would be intriguing to extend the model to multi-attribute decisions where value contains an interaction effect, unlike the environment studied here. One possible way to do this could be to estimate an additional fixation bias on the interaction term.

A third limitation is that two assumptions of the model remain untested. Specifically, the attentional effect is assumed to be modulated by the value of the fixated feature, as opposed to a purely additive effect of attention independent of value (e.g., Cavanagh et al., 2014). Although previous work has found this assumption largely holds in simple binary choice data (Smith and Krajbich, 2019), future work should test this assumption in multi-attribute settings. Second, the model assumes the same attentional bias for the unfixated attribute of both options, although this is modulated by the option bias on the unfixated option. Although it is possible to estimate a version of the model that does not make this assumption, more trials would likely be needed in order to reduce the noise associated with the estimation procedure and the relatively small quantitative impact of the attribute bias compared to the option bias.

Declaration of Competing Interest

The author declare that there is no conflict of interest.

Acknowledgments

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Appendix A

Group Model Fit Procedure

The group maximum likelihood procedure was conducted as follows and the likelihood computation is similar to a previous estimation technique first employed in Tavares et al. (2017) that was used to estimate an option fixation bias. Here, we adapt their estimation technique to estimate two fixation biases: one for the unfixated choice option and one for the unfixated attribute, though the underlying logic of the technique is identical.

We defined a grid of parameter combinations over the following set:

d in $\{0.001, 0.002, 0.003, 0.004, 0.005, 0.006, 0.007, 0.008, 0.009, 0.01\}$

σ in $\{0.04, 0.045, 0.05, 0.055, 0.06, 0.065, 0.07, 0.075, 0.08, 0.085, 0.09\}$

θ in $\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$

δ in $\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$

We then computed a likelihood, as described below, for each of the 13,310 parameter combinations in the above set. The time data (including the response times, fixation durations, latencies, and saccades) were binned into 10 ms steps to help reduce the computational cost of the estimation.

In order to compute the likelihood of a trial conditional on choice, response time, and the pattern of observed fixations, we first discretized the RDV into 21 bins of size 0.1 which transformed the model state-space into a two-dimensional table where rows indicated the state of the RDV and columns indicated time, increasing from left to right, in 10 ms intervals. At every point in the table, we filled in the probability of the RDV being in each time bin (as described in the next paragraph) given the model and choice set parameters of a trial, conditional on a decision not having been made at that time.

To begin each simulation, we started at time point zero in the first column of the table and assigned a probability of 1 to the zero-bin, which reflects the assumption that the RDV takes value zero at the beginning of every trial. We next filled in the columns of the table, from left to right, using the following logic. Let P_t^i denote the probability the RDV is in bin i at time t. Then, for all RDV bins j between the +/- 1 evidence thresholds, the probability of the RDV being located in bin j at time $t+1$ is $P_{t+1}^i = \sum_i P_t^i P_t^{i\to j}$, where $P_t^{i\to j}$ is the transition probability from i to j. $P_t^{i\to j}$ can be computed by noticing that the change in the RDV in one time step is $N(\mu,\sigma)$. Before a fixation to a feature, during non-feature fixations, and during any saccades, $\mu = 0$. During feature fixations,

$$\mu = \begin{cases} (P_L + \delta N_L) - \theta(P_R + \delta N_R), \text{fixation to } P_L \\ (\delta P_L + N_L) - \theta(\delta P_R + N_R), \text{fixation to } N_L \\ -((P_R + \delta N_R) - \theta(P_L + \delta N_L)), \text{fixation to } P_R \\ -((\delta P_R + N_R) - \theta(\delta P_L + N_L)), \text{fixation to } N_R \end{cases}$$

hence, $P_t^{i\to j}$ is given by the probability density function $N(\mu,\sigma)$ for γ where γ is the difference in mean RDV values between bins j and i.

Whereas the above describes the state of the RDV at each time assuming a decision is not yet made, we also calculate the probability of the RDV crossing a threshold and a decision being made at each time point. For example, the probability of the model crossing the upper threshold (corresponding to a left choice) at time $t+1$ is $P_{t+1}^{UP} = \sum_i P_t^i P_t^{i\to UP}$ where $P_t^{i\to UP}$ is the probability of the RDV moving from bin i to reaching the upper threshold at time t, which is given by a draw from $N(\mu,\sigma)$ which is greater than $1-i$, and P_{t+1}^{DOWN} is similarly defined as crossing the lower threshold.

Then, for every trial the RDV table is filled out from left to right until the observed response time is reached. The likelihood is given by P_{RT}^{UP} if a left choice was made and P_{RT}^{DOWN} if a right choice was made. Note that the sum of the likelihood at any given RT is not restricted to sum to one as long as there is some probability that a choice can be made before that time.

In the computations, we took the duration of all fixation events in milliseconds and divided by the size of the time bin (i.e., 10 ms). We discarded the remainder in order to allow each corrected fixation event duration to be an exact multiple of our time bin size. This allows each fixation event to terminate at the end of a time bin, simplifying the computations.

Appendix B

Individual Model Fit Procedure

The individual maximum likelihood estimation procedure was identical to the procedure described in the "Group Model Fit Procedure" in Appendix A with the following caveats. First, rather than pooling all data into one pooled data set, we perform the estimation procedure separately for each participant. Second, if the best fitting parameters included a value of d or σ that was a maximum or minimum value over the set of parameters in the search set, we extended the searched parameters to include additional values. This only occurred for three participants. The results are reported below in Appendix Table 1.

Appendix Table 1

Participant ID	d	σ	δ	θ	LL
102	0.004	0.06	1	0.5	−879.32
104	0.003	0.05	0.9	0.8	−880.90
105	0.004	0.075	0.6	0.7	−886.81
108	0.001	0.065	1	0.4	−844.89
109	0.004	0.07	1	0.5	−899.76
110	0.004	0.06	0.8	0.8	−897.16
111	0.020	0.11	0.9	0.4	−635.18
114	0.005	0.075	0.4	0.3	−830.83
115	0.007	0.07	0	0.9	−910.87
116	0.005	0.06	0.8	0.5	−879.75
118	0.004	0.07	0.8	0.7	−860.28
120	0.003	0.055	1	0.9	−889.70

(continued on next page)

Appendix Table 1 (*continued*)

Participant ID	d	σ	δ	θ	LL
121	0.007	0.075	0.8	0.8	−858.08
122	0.004	0.055	0.9	0.9	−862.08
123	0.006	0.055	0.9	0.8	−826.76
124	0.005	0.08	0.6	0.4	−859.94
125	0.009	0.085	0.4	0.7	−797.42
126	0.004	0.08	0.9	0.2	−848.98
128	0.005	0.085	1	0.9	−828.18
129	0.004	0.07	0.2	0.9	−868.48
132	0.005	0.055	0.7	0.6	−891.76
133	0.005	0.06	0.4	0.5	−851.86
134	0.007	0.075	0.2	0.6	−863.33
135	0.003	0.04	0.5	0.2	−918.32
136	0.004	0.085	0.5	0.7	−839.09
137	0.003	0.075	1	0.5	−848.82
138	0.008	0.085	0.9	0.2	−664.76
139	0.003	0.085	0	0	−842.40
141	0.005	0.055	0.2	0.5	−876.83
142	0.008	0.085	0.1	0.3	−748.82
143	0.004	0.07	1	0.6	−845.43
144	0.003	0.10	1	0	−811.84
146	0.002	0.085	0.9	0	−812.32
147	0.006	0.075	1	0.6	−847.98

Note: Individual model estimates for the best fitting unrestricted model. LL denotes the log-likelihood.

Appendix C

Heterogeneity of Model Parameters and Fixation Strategies

To examine whether individual differences in model parameters were associated with differences in search strategies, as suggested, we looked at the correlation between each of the four estimated model parameters (i.e., δ, θ, σ, and d) at the individual level and search strategies in several ways.

First, we looked at the correlation between each model parameter and the average number of types of saccades made by each participant. We did not find any significant relationship between δ or θ and search strategies (δ: total attribute-based saccades: $\beta = -0.0$, $p = 0.988$, total option-based saccades: $\beta = 0.4$, $p = 0.401$; θ: total attribute-based saccades: $\beta = 0.5$, $p = 0.180$, total option-based saccades: $\beta = 0.9$, $p = 0.086$). This suggests the fixation bias parameters were not influenced by search strategy. The marginally significant result provides some weak evidence that the propensity to search within an option is correlated with less discounting of options. However, we did find a relationship between both d and σ and search strategies (d: total attribute-based saccades: $\beta = -101.3$, $p = 0.002$, total option-based saccades: $\beta = -152.4$, $p < 0.001$; σ: total attribute-based saccades: $\beta =$ –33.5, $p < 0.001$, total option-based saccades: $\beta = -41.6$, $p < 0.001$). This latter analysis suggests more attribute or option saccades were both associated with a slower slope accumulation towards a boundary and less noise in the decision process.

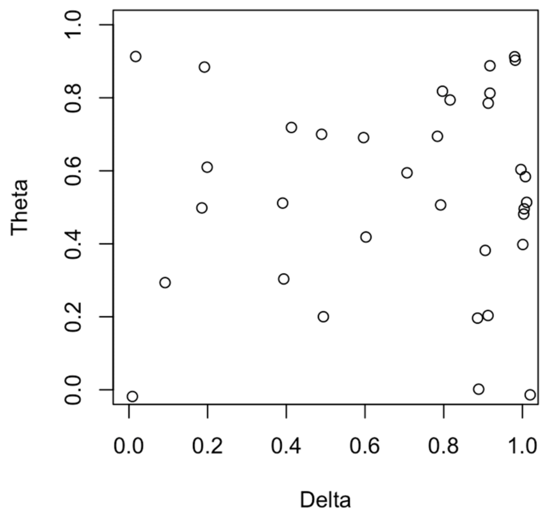
Second, we looked at the relationship between search strategies, as measured by relative saccade patterns, and model parameters. In this analysis, we did not find a significant association between the search and model parameters (δ: relative attribute-based saccades: $\beta = -0.1$, $p = 0.143$, relative option-based saccades: $\beta = 0.0$, $p = 0.147$; θ: relative attribute-based saccades: $\beta = -0.0$, $p = 0.846$, relative option-based saccades: $\beta = 0.0$, $p = 0.641$) and (d: relative attribute-based saccades: $\beta = -0.0$, $p = 0.995$, relative option-based saccades: $\beta = -2.1$, $p = 0.481$; σ: relative attribute-based saccades: $\beta = -0.7$, $p = 0.407$, relative option-based saccades: $\beta = -0.3$, $p = 0.621$).

Third, we clustered participants based on their search strategies to examine (1) whether clustering provided a reasonable separation of a participant's search strategy (i.e., propensity to make more attribute-based vs. option-based saccades) and (2) whether clusters were associated with differences in estimated model parameters. To do this, we conducted a k-means clustering analysis and set $k = 2$ so that participants were clustered into one of two groups. We conducted this analysis by clustering on the type of saccades, as done in Reeck et al. (2017).

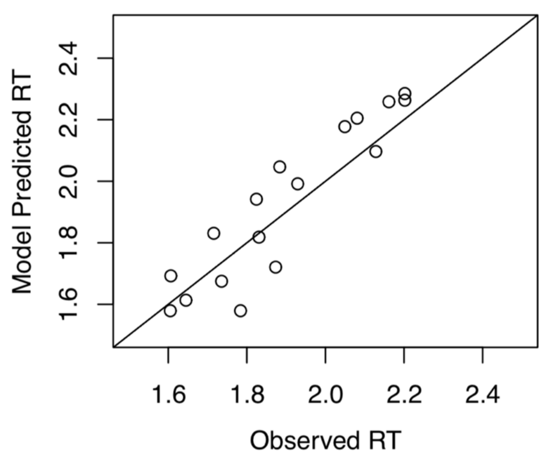
Cluster 1 contained 19 participants and Cluster 2 contained 15 participants. We found that Cluster 1 made more attribute-based (Cluster 1 mean: 1.93, Cluster 2 mean: 1.13; $t(28.7) = 6.05$, $p < 0.001$) and more option-based (Cluster 1 mean: 2.58, Cluster 2 mean: 1.43; $t(32.0) = 5.07$, $p < 0.001$) transitions, suggesting clustering operates based on the number of saccades, rather than the type of saccade. In fact, there was no difference between the relative proportion of attribute-based saccades (Cluster 1 mean: 39.0%, Cluster 2 mean: 39.8%; $t(29.4) = 0.38$, $p = 0.707$) or option-based saccades (Cluster 1 mean: 50.6%, Cluster 2 mean: 49.2%; $t(31.7) = 0.80$, $p = 0.429$). Overall, it appears that Cluster 1 made more saccades but did not exhibit a search strategy that was more attribute-based or option-based, compared to Cluster 2.

Finally, we examined whether there were any differences in estimated model parameters between the clusters. We found that the clusters differed in their estimated σ (Cluster 1 mean: 0.06, Cluster 2 mean: 0.08; $t(27.0) = 4.79$, $p < 0.001$) and θ (Cluster 1 mean: 0.63, Cluster 2 mean: 0.43; $t(25.5) = 2.18$, $p = 0.039$), but not in their estimated d (Cluster 1 mean: 0.004, Cluster 2 mean: 0.006; $t(16.3) = 1.55$, $p = 0.141$) or δ (Cluster 1 mean: 0.71, Cluster 2 mean: 0.65; $t(27.8) = 0.488$, $p = 0.629$). This suggests that the cluster that searched more (i.e., Cluster 1) had significantly less noise enter the decision process and less discounting in the value of the unattended option.

Appendix D



Appendix Fig. 1. Individual estimates of δ and θ. Each point represents a participants' estimate of the two parameters from Appendix Table 1. Note that a small amount of noise was added to each point (i.e., jittered) so that participants with identical estimates could be differentiated.



Appendix Fig. 2. Observed versus model predicted response times. Each point plots the mean response time for a type of trial based on the difference in liking ratings. The 45 degree line is plotted to aid comparison. Response time plotted in seconds.

Appendix E. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.obhdp.2021.04.004.

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