A dynamic computational model of gaze and choice in multi-attribute decisions

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ABSTRACT

When making decisions, how people allocate their attention influences their choices. One empirical finding is that people are more likely to choose the option that they have looked at more. This relation has been formalized with the attentional drift-diffusion model (aDDM; Krajbich et al., 2010). However, options often have multiple attributes, and attention is also thought to govern the relative weighting of those attributes (Roe et al., 2001). Little is known about how these two distinct features of the choice process interact; we still lack a model (and tests of that model) that incorporate both option- and attribute-wise attention. Here, we propose a multi-attribute attentional drift-diffusion model (maaDDM) to account for attentional discount factors on both options and attributes. We then use five eye-tracking datasets (two-alternative, two-attribute preferential tasks) from different choice domains to test the model.

We find very stable option-level and attribute-level attentional discount factors across datasets, though non-fixated options are consistently discounted more than non-fixated attributes. Additionally, we find that people generally discount the non-fixated attribute of the non-fixated option in a multiplicative way, and so that feature is consistently discounted the most. Finally, we also find that gaze allocation reflects attribute weights, with more gaze to higher-weighted attributes. In summary, our work uncovers an intricate interplay between attribute weights, gaze processes, and preferential choice.

Keywords: attention, decision making, computational modelling, drift diffusion model, eye tracking, multi-attribute
**Introduction**

Many decisions we make involve tradeoffs between attributes. These decision attributes often conflict, for example when deciding whether to eat a tasty but unhealthy pizza or a healthy but less tasty salad, whether to buy an affordable but generic piece of clothing or a pricy but luxurious one, or whether to travel and risk getting sick or to stay home and be safe. A key determinant of peoples’ decisions is thus how they weight these attributes. Inferring attribute weights from choices is a standard methodology for characterizing people’s decisions (Goldstein, 1990). These attribute weights may be constant over the course of the decision or may vary dynamically.

Evaluating attribute values requires attending to them, deciding whether they are desirable, and incorporating them into the decision. Therefore, it has been argued that attention may play an important role in attribute weighting (Bhatia, 2017; Busemeyer & Townsend, 1993; Diederich, 1997; Johnson et al., 2007; Maier et al., 2020; Roe et al., 2001; Weber et al., 2016).

Some research has used eye-tracking data to confirm that shifts in attention between attributes are predictive of decision outcomes (Russo & Dosher, 1983; Russo & Rosen, 1975; Amasino et al., 2019; Fisher, 2017; Glickman et al., 2019; Noguchi & Stewart, 2014; Reeck et al., 2017; Rramani et al., 2020; Westbrook et al., 2020). Thus, the interplay between attribute weighting and the gaze process is crucial for model development in decision science (Busemeyer et al., 2019; Krajbich, 2019; Turner et al., 2018).

There has already been some progress in modeling the role of gaze in single-attribute choice (Ashby et al., 2016; Cavanagh et al., 2014; Krajbich et al., 2010) and in some specific multi-attribute cases (Amasino et al., 2019; Fisher, 2017; Glickman et al., 2019; Westbrook et
al., 2020). However, we still lack a domain-general model for how to account for gaze to both options and attributes in two-alternative forced choice. That is the aim of this paper.

**Attention to options and attributes**

A large body of work has established the importance of overt visual attention in value-based decisions (Krajbich, 2019). This research has shown that gaze is involved in preference formation, amplifying the values of attended options. The amount of gaze to an option (as measured with fixation/dwell times) increases the probability of choosing that option in various choice domains (Smith & Krajbich, 2018). This also yields what is known as the gaze cascade effect, where people tend to choose items that they have most recently viewed (Krajbich et al., 2010; Mullett & Stewart, 2016; Shimojo et al., 2003). Other work has studied how manipulating gaze can bias choices (Armel et al., 2008; Ghaffari & Fiedler, 2018; Gwinn et al., 2019; Lim et al., 2011; Newell & Le Pelley, 2018; Pärnamets et al., 2015; Tavares et al., 2017; Towal et al., 2013)

Despite these findings, most work has only established the connection between gaze and decision making at the option-level. There has been less focus on the connection between attribute-level gaze and choice (Amasino et al., 2019; Fisher, 2017; Glickman et al., 2019; Pachur et al., 2018; Westbrook et al., 2020). More critically, the relationship between contributions of option-level and attribute-level attention towards choice remains unclear.

In terms of choices involving multiple attributes, it is often true that one attribute is more important than the other(s). Researchers typically assume that more important attributes will receive more attention (Diederich, 1997; Roe et al., 2001), consistent with eye-tracking findings in multi-attribute choice (Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Hristova &
Grinberg, 2008; Teoh et al., 2020). However, it is unclear whether attribute weights are fully reflected by gaze. For example, when deciding between foods that differ in taste and health, if a decision-maker spends 70% of their time looking at the food and 30% examining its nutritional information, does that imply a weight of 0.7 on taste and 0.3 on health?

**Models of attention in value-based choices**

Models of decision making based on sequential sampling processes have become dominant in cognitive science, and the application of sequential sampling models (SSMs) to value-based decisions have become increasingly commonplace. SSMs assume that decision makers accumulate evidence over the course of the decision-making process. A decision is made when the evidence reaches a threshold. SSMs provide accounts for both choices as well as response times (Ratcliff & Smith, 2004). Several prominent SSMs have been developed to capture multi-attribute and multi-alternative decisions: Multi-alternative Decision Field Theory (MDFT, Busemeyer & Townsend, 1993; Diederich, 2003; Roe et al., 2001), Multi-attribute Linear Ballistic Accumulator (MLBA, Trueblood et al., 2014), Associative Accumulator (AAM, Bhatia, 2013), and Multi-attribute Leaky Competing Accumulator (MLCA, Usher & McClelland, 2001). Some of these modeling frameworks assume that attention drives attribute weights. For instance, MDFT and MLCA argue that attention shifts between attributes over time, thus changing the sequential sampling process. Meanwhile, other sequential sampling models, such as MLBA, treat attention weight to each attribute as a free parameter in the model. The attentional assumptions of these SSMs have not been tested with eye-tracking data.

As the link between attention and choice has garnered more interest, researchers have begun to include process data into the SSM framework. For example, the relationship between
option-level gaze and choice has been well-captured by the attentional drift diffusion model (aDDM) and its extensions (Gluth et al., 2020; Krajbich & Rangel, 2011; Tavares et al., 2017; Towal et al., 2013; Vaidya & Fellows 2015). However, the aDDM doesn’t specify the relationship regarding attentional discounts at the attribute level.

Another model, the baDDM presented by Fisher (2017), reflects the relationship between attribute-level gaze and choices: gaze to an attribute increases its weight and so influences the final decision. However, this model only applies to single-alternative decisions, namely whether to accept or reject an option with both positive and negative attributes. Therefore, this model cannot account for attention to both attributes and options.

In this paper we introduce a new model, the multi-attribute aDDM (maaDDM), to account for gaze to both options and attributes. We use eye tracking to measure gaze allocation and we then incorporate it into the choice model. With this model, we are able to test whether there is a relationship between option-level and attribute-level attentional effects. We can additionally ask what happens to non-fixated attributes of non-fixated options: do they get doubly discounted, or is there a single discount factor that is applied to all options on the non-fixated attribute, or is there a single discount factor that is applied to all attributes of the non-fixated option? We can also investigate to what extent attribute gaze reveals attribute weights.

To test our model, we used five eye-tracking datasets from different choice domains, each with two-options and two attributes. Some tasks had symmetric attributes (e.g., 50/50 gambles with two possible outcomes) while others had distinct attributes (e.g. items of clothing with separate brand labels). These datasets were collected from three different labs, for other projects.
To preview the results, we find that attribute-level gaze plays an important role in the decision process, though less so than option-level gaze. We also find that the non-fixated attribute of the non-fixated option is discounted the most. Specifically, it is doubly discounted, consistent with receiving both the attribute- and option-level discounts. With regards to the relationship between attribute gaze and attribute weight, we find that gaze dwell time does reflect attribute weights, which suggests that gaze is drawn to more important attributes. But we also find that additional attribute weights are still necessary even after accounting for gaze, at least for meaningfully different attributes (e.g., clothing appearance vs. brand labels).

Methods

Data

We used data from five, two-alternative, two-attribute datasets. Two of these datasets comprised choices between 50-50 gambles. In one task the outcomes were monetary and in the other they were snack foods (Smith & Krajbich, 2018). Here the two “attributes” were simply the two outcomes of each gamble. We refer to these as symmetric attributes. The other three datasets involved choices between options with meaningfully different attributes, including divisions of money between oneself and another (social value orientation / mini dictator game) (Smith & Krajbich, 2018), clothing items coupled with brand labels (based on Philistides & Ratcliff, 2013), and snack foods coupled with their nutrition labels (Rramani et al., 2020). Every study included eye-tracking. Some data supporting this study were taken from Smith & Krajbich (2018) and Rramani et al. (2020). Data and analysis code are available at https://osf.io/d7s6c/ (Yang & Krajbich, 2021). This study was not preregistered.
Food gamble, money gamble, & dictator game

Three datasets were previously published in Smith & Krajbich (2018). In that study, 44 subjects completed six different tasks, including four two-alternative forced choice tasks. In addition to the three tasks described above, subjects also completed a two-food choice task, as well as an initial food-rating task, and a final psychophysics task. Eight of the subjects completed an alternate version of the monetary-risk and dictator-game tasks; that data was excluded in the original publication and here. The study was conducted at the Ohio State University and was approved by the Ohio State Institutional Review Board.

Subjects in this study first rated their desire to consume 147 food items on a scale from -10 to 10. They were then calibrated on the eye-tracker and then proceeded on to the four choice tasks, which were randomized in a blocked design. The aim was to have 200 trials in each task, but in some cases there were fewer trials in the food choice tasks (only positively rated foods were included; the average number of trials in the food gamble task was 147). Each trial consisted of a choice between options on the left and right sides of the screen. Subjects indicated their choice with a keyboard press: F and J for the left and right option respectively.

In the food gamble task (Fig. 1a), subjects chose between two 50/50 gambles involving food items. In the money gamble task (Fig. 1b), subjects chose between two 50/50 gambles involving dollar amounts ranging from $0 to $10.

In the dictator game (Fig. 1c), subjects chose between two divisions of money between themselves and the next subject in the study. Each option consisted of a payoff for the subject (in red) and a payoff for the next subject (in blue); these amount ranged from $0 to $5. The vertical positions of the payoffs were counterbalanced across subjects. In addition, there were two types
of trials in the dictator game – “compassion” trials and “envy” trials, and these two trial types were randomly intermixed within the task. In the compassion trials, subjects’ payoffs were always higher than the receivers’; in the envy trials subjects’ payoffs were always lower than the receivers’. There is a distinction between these two regimes in the literature (Fehr & Schmidt 1999; Morishima et al. 2012), and so here we considered them separately. There were 83 compassion trials and 117 envy trials for each subject. Following Smith & Krajbich (2018), we excluded 14 selfish subjects who nearly always chose the selfish option.

After completing all the choice tasks, subjects completed a final psychophysics task designed to measure tunnel vision. We do not analyze that data here (but see Smith & Krajbich 2018 for details). Then, subjects received a $5 show-up fee, a snack food they chose from one randomly selected trial in the food choice tasks, additional money from the options they chose in one randomly selected money risk trial and dictator game trial, as well as additional money from the prior subject’s selected dictator game trial.

**Food + nutrition labels**

In this study, 50 subjects made incentivized choices between snack foods presented with their nutrition labels. Subjects first rated each of 100 foods based on how much they liked their taste on a scale from −4 (not at all) to 4 (very much). In this part of the experiment, the products were shown without any nutrition labels. There was no time limit in this task.

Subsequently, subjects made choices between healthy and unhealthy items. The nutrition labels were presented below the food items (Fig. 1d-e). There were 120 trials with grey guideline-of-daily-amount (GDA) labels and 120 trials with color coded traffic-light (TL) labels. In total, there were five blocks of 48 trials each, and GDA/TL trials were randomly intermixed
throughout these blocks. Participants indicated their choice by pressing computer keys with their corresponding index fingers. If a subject did not make a choice within 20 s, the experiment proceeded automatically to the next trial. To avoid possible effects of the brand information the brand names on the products were covered up. Trials were separated by a fixation cross shown on a black background for 1s.

There were five pieces of information in the nutrition labels: calories (no color coding), sugar, fat, saturated fat, and salt. Colors could be green, yellow, and red, with green indicating healthy, yellow neutral, and red unhealthy. We used positive/negative numbers to represent healthy/unhealthy components (red = -1; yellow = 0; green = 1), and then summed up the four components to calculate the overall health score for each item.

There were also 240 trials with scrambled/unintelligible nutrition labels, as well as a willingness-to-pay task at the end of the study. We did not include these data in our analysis. The dataset was collected at the University of Bonn. The local ethics committee of the university approved the study.

Clothing + brands

In this study, 28 subjects made hypothetical choices between clothing items paired with brand labels. First, subjects provided liking ratings for 180 clothing items taken from the websites of popular UK retail clothing stores. Items were presented without brand information. Subjects indicated their ratings on a scale from -3 (really dislike) to 3 (really like). Next, subjects ranked 24 brand logos (also from popular UK retailers) from most to least preferred. The four brands in the middle of the ranking were excluded from the rest of the task. There were no time limits in either task.
Subsequently, subjects made choices between item-brand pairs. The brands were displayed above the clothing items, with a 60 pixel gap between them (Fig. 1f). Each trial was constructed so that one item had a brand ranked 1-10 and one ranked 15-24, and also so that the difference in ratings between the clothing items was no greater than 3. Specifically, there were 50 trials per rating difference, resulting in a total of 350 trials. Subjects had 5 seconds to indicate their choice using the left or right mouse button. Between trials there was a 1.2 s ITI followed by 1 s of enforced fixation at the center of the screen. Eye-movement data was recorded with an EyeLink1000 eye-tracker sampled at 1000 Hz. The study was conducted at the University of Glasgow and was approved by the local ethics board.

Figure 1. Experiments. Every task involved a choice between one option on the left and another on the right. (a) The food gamble task involved 50/50 gambles with one food outcome on the top and one outcome on the bottom. (b) The money gamble task involved 50/50 gambles with one monetary outcome on the top and one outcome on the bottom. The height of the white bars indicated the amount of money. (c) The dictator game involved allocations of money between oneself (in red) and another participant (in blue). The height of the bars indicated the amount of money. (d) The food + nutrition task with TL nutrition labels had color coded nutrition labels beneath the food images. (e) The food + nutrition task with GDA nutrition labels had monochrome nutrition labels below images of the food items. (f) The clothing + brand task had brand labels above images of the clothing items.
Subjects in this study also made choices in 350 labels-absent trials. These trials were interleaved with the labels-present trials, but used a different set of clothing items and phased scrambled labels. We did not include this set of choices in our analysis.

Model Specification

Our model is based on the sequential sampling framework, which conceptualizes decision-making as a noisy process accumulating evidence over time, with a decision being made when the relative evidence (of one alternative over the other) reaches a decision threshold (Ratcliff, 1978). This framework has been extended to value-based decision making with a number of models. Most relevant here are Decision Field Theory (DFT) and the attentional Drift Diffusion Model (aDDM). DFT assumes that attention fluctuates between attributes, altering the weights on those attributes in the evidence accumulation process. The aDDM assumes that attention (specifically gaze) shifts between options, amplifying the evidence coming from the fixated option. Given this, we set out to build a model to account for gaze shifts between both options and attributes during the decision-making process.

For simplicity, assume that choices comprise two alternatives $W \in \{X, Y\}$ and two attributes $i \in \{A, B\}$. A simple application of the aDDM would yield the following drift rates:

\[(X_A - \theta Y_A) + (X_B - \theta Y_B)\] when looking at option X, and

\[(\theta X_A - Y_A) + (\theta X_B - Y_B)\] when looking at option Y

where $W_i$ is the value of option $W$ on attribute $i$, and $\theta$ is the discount factor on the non-fixated option.

If instead we assume attribute-wise attention (as in DFT) we can apply a similar discount to the non-fixated attribute, yielding the following drift rates:
\[(X_A - Y_A) + \phi(X_B - Y_B)\] when looking at attribute A, and
\[\phi(X_A - Y_A) + (X_B - Y_B)\] when looking at attribute B

where \(\phi\) is the discount factor on the non-fixated attribute.

By simply combining these two model features, we arrive at a model that discounts both the non-fixated option and the non-fixated attribute (Fig. 2). For example, when looking at attribute A of option X, we would have the following drift rate:

\[(X_A - \theta Y_A) + \phi(X_B - \theta Y_B)\]

In this model, the non-fixated attribute of the non-fixated option gets discounted by \(\theta \phi\); from now on we refer to this element as the “diagonal” element. In other words, the diagonal element gets discounted twice. Of course, gaze discounting may not operate in such a multiplicative manner. Both attributes of the non-fixated option may be discounted equally, or both options may be discounted equally on the non-fixated attribute. Or, there could be some other discount factor on the diagonal element. To investigate these hypotheses, we generalize the model by adding a third gaze discounting parameter \(\gamma\) for the diagonal element. For example, when looking at attribute A of option X, we would have the following drift rate:

\[X_A - \theta Y_A + \phi X_B - \gamma Y_B\]

We can then test whether \(\gamma = \theta \phi\), \(\gamma = \phi\), \(\gamma = \theta\), or \(\gamma\) = unconstrained, provide the best fit to the data.

As mentioned earlier, attribute weights may not simply be driven by gaze. To test if gaze can fully account for the attribute weights, we introduce another parameter \(\omega\). In the model, we assume \(\omega\) is the weight on attribute A and \(1 - \omega\) is the weight on attribute B, respectively. For example, when looking at \(X_A\) the drift rate would be:

\[\omega(X_A - \theta Y_A) + (1 - \omega)(\phi X_B - \gamma Y_B)\]
and when gaze is turned to $Y_B$ the drift rate would be:

$$\omega(\gamma X_A - \phi Y_A) + (1 - \omega)(\theta X_B - Y_B)$$

**Figure 2. Illustration of the model.** The relative decision value starts out halfway between the barriers for the two options. Over time, the relative decision value evolves at a rate that depends on which piece of information (i.e. element) is fixated, indicated here by the colored vertical segments. When the relative decision value reaches one of the barriers, the corresponding choice is made. Fixating on attributes of the left option generally pushes the relative decision value upwards towards the left barrier, while fixating on the right option generally pushes it downwards towards the right barrier.

**Model fitting**

Choice, eye-tracking, and response time (RT) data were used to fit the models. Trials with missing eye-tracking data were removed. As a result, on average there were 143 trials in the food gamble task ($SD_{trial} = 44$); 176 trials in the money gamble task (SD = 34); 167 trials in the dictator game ($SD_{trial} = 16$; compassion: $M_{trial} = 62$ $SD_{trial} = 6$; envy: $M_{trial} = 105$, $SD_{trial} = 10$); 188 trials in the food & nutrition label task ($SD_{trial} = 14$; GDA label: $M_{trial} = 95$, $SD_{trial} = 6$; TL label: $M_{trial} = 94$, $SD_{trial} = 8$); 347 trials in the clothing + brand task ($SD_{trial}$
=3) per subject. Following Cavanagh et al. (2014), we tested our model by re-expressing the drift rate in terms of gaze proportion and individual elements’ values. These values were based on the objective dollar amounts in the gamble task and dictator games, on the objective healthiness of the foods in the food + nutrition label task, and otherwise on subject ratings/rankings of the foods, clothing items, and clothing brands (see Supplementary Note 3). All values were re-scaled from 1 to 10 in each dataset.

The models were fit to choice and RT distributions using RSTAN (Carpenter et al., 2017) combined with RWiener (Wabersich & Vandekerckhove, 2014). For each trial, we first transformed the sequence of fixation-dependent drift rates into a single, constant drift rate. Then, the RT on trial \(i\) follows the Wiener first passage time distribution

\[
RT_i \sim \text{wiener} \left( a, t_{er}, z, \delta \right)
\]

where \(a\) is the boundary separation, \(t_{er}\) is the non-decision time, \(z\) is the starting-point bias, and \(\delta\) is the drift rate. We fixed \(z\) at 0.5 in all the models, assuming no starting-point bias towards the left option. We also generated log pointwise predictive density from the MCMC samples for later model comparison. Four chains of 5000 samples were generated; the first 2500 samples were discarded as burn-in. The fitting results were based on combined samples from each chain.

It is worth noting that the assumption of a single drift rate per trial approximates the true data-generating process in which the drift rate changes with each new fixation. We adopted this approximation to facilitate model fitting. To ensure that this approximation would not bias our results, we performed a parameter-recovery exercise where we simulated data with the “true” attention-switching model and then fit those data with our constant drift rate approximation. We found little distortion in the recovered model parameters (see Supplementary Note 2).
Model parameters were estimated separately for each individual in each data set. For each subject, we excluded trials where the logarithm of RT in this trial was two standard deviations above its mean or shorter than 300ms. Additionally, we excluded subjects who had less than 80 trials or who averaged less than two fixations per trial. This left us with 42 out of 44 subjects in the food gamble task \((M_{\text{trial}}=137, SD_{\text{trial}} = 41)\), 33 out of 36 subjects in the money gamble task \((M_{\text{trial}}=168, SD_{\text{trial}} = 33)\), 20 out of 22 subjects in the dictator game (compassion: \(M_{\text{trial}}= 59, SD_{\text{trial}} = 5\); envy: \(M_{\text{trial}} = 100, SD_{\text{trial}} = 9\)), 48 out of 50 subjects in the food + nutrition label task (GDA: \(M_{\text{trial}} = 89, SD_{\text{trial}} = 6\); TL: \(M_{\text{trial}} = 90, SD_{\text{trial}} = 5\)), and 28 out of 28 subjects in the clothing + brand task \((M_{\text{trial}}=330, SD_{\text{trial}} = 5)\).

**Results**

Before turning to the modeling, it is useful to summarize some basic behavioral results in each dataset. This provides a sanity check for the model results and a baseline to compare against. As mentioned above, to be consistent, we rescaled subjective values from 1 to 10 for each element.

First, we investigated the weights that subjects appeared to assign to the two attributes, without accounting for gaze. To do so, we ran a logistic regression of *choose left option* (1 or 0) on *Attribute A value difference* (left – right) and *Attribute B value difference* (left – right) at the subject level, within each task. We then assumed the weight on Attribute A is \(\omega^*\), and the weight on Attribute B is \(1 - \omega^*\). We checked if \(\omega^*\) was significantly different from 0.5 in each

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1 In the dictator game, we separately fitted the compassion and envy trials. However, there were fewer compassion trials \((M = 62)\) than envy trials \((M = 105)\). Therefore, we only applied the exclusion criterion to the envy case.

2 We ran this regression in Stan with the uniform priors, to allow for comparison with later results in the *Attribute weight* section.
A dynamic computational model of gaze and choice task using two-tailed t-tests. The results indicated that \( \omega^* \) was significantly different from 0.5 in all datasets except in the food and money gamble tasks (Table 1, column 1).

### Table 1

**Behavioral results: Means and 95% Confidence Intervals (in parentheses) of the test statistics/coefficients in the text.**

<table>
<thead>
<tr>
<th></th>
<th>( \omega^* )</th>
<th>RT effect Attribute A</th>
<th>RT effect Attribute B</th>
<th>Gaze-based attribute weight</th>
<th>Gaze-based option weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food gamble</td>
<td>0.52</td>
<td>-0.039***</td>
<td>-0.023***</td>
<td>0.10**</td>
<td>1.01***</td>
</tr>
<tr>
<td></td>
<td>[0.50, 0.54]</td>
<td>[-0.052, -0.026]</td>
<td>[-0.035, -0.011]</td>
<td>[0.026, 0.17]</td>
<td>[0.80, 1.20]</td>
</tr>
<tr>
<td>Money gamble</td>
<td>0.51</td>
<td>0.018</td>
<td>-0.0039</td>
<td>0.096*</td>
<td>1.13***</td>
</tr>
<tr>
<td></td>
<td>[0.50, 0.51]</td>
<td>[-0.037, 0.0015]</td>
<td>[-0.023, 0.015]</td>
<td>[0.0061, 0.19]</td>
<td>[0.89, 1.38]</td>
</tr>
<tr>
<td>Dictator game:</td>
<td>0.74***</td>
<td>-0.025</td>
<td>-0.033†</td>
<td>0.17*</td>
<td>1.19***</td>
</tr>
<tr>
<td>compassion</td>
<td>[0.69, 0.79]</td>
<td>[-0.073, 0.024]</td>
<td>[-0.065, -0.0003]</td>
<td>[0.0042, 0.35]</td>
<td>[0.90, 1.49]</td>
</tr>
<tr>
<td>Dictator game:</td>
<td>0.90***</td>
<td>-0.064***</td>
<td>-0.030*</td>
<td>0.14</td>
<td>0.79***</td>
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<tr>
<td>envy</td>
<td>[0.87, 0.93]</td>
<td>[-0.098, -0.031]</td>
<td>[-0.055, -0.0052]</td>
<td>[-0.083, 0.37]</td>
<td>[0.51, 1.07]</td>
</tr>
<tr>
<td>Food + GDA label</td>
<td>0.84***</td>
<td>-0.12***</td>
<td>-0.042***</td>
<td>0.15*</td>
<td>1.25***</td>
</tr>
<tr>
<td></td>
<td>[0.79, 0.88]</td>
<td>[-0.14, -0.095]</td>
<td>[-0.060, -0.025]</td>
<td>[0.024, 0.28]</td>
<td>[1.049, 1.46]</td>
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<tr>
<td>Food + TL label</td>
<td>0.78***</td>
<td>-0.089***</td>
<td>-0.045***</td>
<td>0.16*</td>
<td>1.21***</td>
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<tr>
<td></td>
<td>[0.73, 0.83]</td>
<td>[-0.12, -0.063]</td>
<td>[-0.060, -0.031]</td>
<td>[0.036, 0.29]</td>
<td>[1.015, 1.39]</td>
</tr>
<tr>
<td>Clothing + Brand</td>
<td>0.81***</td>
<td>-0.053***</td>
<td>0.0022</td>
<td>0.079*</td>
<td>1.43***</td>
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<tr>
<td></td>
<td>[0.76, 0.85]</td>
<td>[-0.066, -0.042]</td>
<td>[-0.0091, 0.013]</td>
<td>[0.0038, 0.15]</td>
<td>[1.14, 1.71]</td>
</tr>
</tbody>
</table>

*Note. \( \omega^* \) represents the attribute weight on Attribute A versus Attribute B, namely the top versus the bottom row in the food gamble and the money gamble task; self versus others in the dictator game; taste versus nutrition in the food + nutrition task; clothing appearance versus brand in the clothing + brand task. See supplement Note 5 for the full version of the regressions.*

† \( p < 0.1 \); * \( p < 0.05 \); ** \( p < 0.01 \); *** \( p < 0.001 \)

We also checked the basic DDM prediction that RT should decrease with the absolute value difference between the options. We ran a mixed-effects logistic regression of \( \log(\text{RT}) \) (in milliseconds) on \textit{absolute Attribute A value difference} (| left – right |) and \textit{absolute Attribute B}
value difference ($|\text{left} - \text{right}|$) within each task. In most cases we observe the expected negative effect (Table 1, columns 2-3).

Next, we tested a prediction of DFT, which is that more attention to an attribute should lead to more weight on that attribute. Here we ran a mixed-effects logistic regression of \textit{choose better option on Attribute A} (1 or 0) on \textit{absolute attribute A value difference, attribute B value difference} (relative to attribute A, i.e., positive when it is in line with attribute A), and \textit{gaze proportion on Attribute A} (within each task). We found the expected positive relationship between attribute gaze proportion and choice in every dataset except in the dictator game (Table 1, column 4).

Finally, we tested a basic prediction of the aDDM, which is that more gaze to Option X vs. Option Y leads to a higher probability of choosing Option X, irrespective of the attribute. Here we ran a mixed-effects logistic regression of \textit{choose left option} (1 or 0) on \textit{Attribute A value difference} (left – right), \textit{Attribute B value difference} (left – right), and \textit{gaze proportion difference} (left – right) within each task. We observed the expected positive relationship between option-level gaze proportion and choice in every dataset (Table 1, column 5).

\textbf{Attribute weights}

One of the assumptions in DFT is that attention determines the weights on attributes during the sequential sampling process (Roe et al., 2001). The most extreme interpretation of this prediction is that attention should fully determine the effect of an attribute on choice. That is, after accounting for gaze, the weights on the attributes should be equal. This would imply that we could infer a person’s attribute weighting from only their gaze proportions.
We tested this hypothesis by asking whether $\omega$ equals 0.5 in the full model with two-tailed t-tests against 0.5 (Table 2, column 4). The group mean was not significantly different from 0.5 in the food gamble task, money gamble, or the compassion trials of the dictator game.

In contrast, $\omega$ was significantly different from 0.5 in the envy trials of the dictator game, the food + GDA label trials, the food + TL label trials, and the clothing + brand task (all $p < 10^{-9}$).

Table 2
Full model results: Means and 95% Confidence Intervals (in parentheses) of parameter estimates from the full model

<table>
<thead>
<tr>
<th></th>
<th>$d$</th>
<th>$t_{er}$</th>
<th>$\sigma$</th>
<th>$\omega$</th>
<th>$\theta$</th>
<th>$\phi$</th>
<th>$\gamma$</th>
</tr>
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<tbody>
<tr>
<td>Food gamble</td>
<td>0.00043</td>
<td>770</td>
<td>0.023</td>
<td>0.52</td>
<td>0.35</td>
<td>0.61</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>[0.00037, 0.00048]</td>
<td>[672, 870]</td>
<td>[0.021, 0.026]</td>
<td>[0.50, 0.55]</td>
<td>[0.29, 0.40]</td>
<td>[0.55, 0.66]</td>
<td>[0.24, 0.33]</td>
</tr>
<tr>
<td>Money gamble</td>
<td>0.00052</td>
<td>584</td>
<td>0.024</td>
<td>0.48</td>
<td>0.41</td>
<td>0.59</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>[0.00045, 0.00059]</td>
<td>[492, 677]</td>
<td>[0.021, 0.027]</td>
<td>[0.45, 0.52]</td>
<td>[0.31, 0.50]</td>
<td>[0.51, 0.68]</td>
<td>[0.36, 0.55]</td>
</tr>
<tr>
<td>Dictator game:</td>
<td>0.00064</td>
<td>691</td>
<td>0.025</td>
<td>0.51</td>
<td>0.46</td>
<td>0.55</td>
<td>0.36</td>
</tr>
<tr>
<td>compassion</td>
<td>[0.00055, 0.00073]</td>
<td>[577, 806]</td>
<td>[0.022, 0.027]</td>
<td>[0.38, 0.65]</td>
<td>[0.39, 0.53]</td>
<td>[0.47, 0.62]</td>
<td>[0.28, 0.43]</td>
</tr>
<tr>
<td>Dictator game:</td>
<td>0.00078</td>
<td>676</td>
<td>0.026</td>
<td>0.94</td>
<td>0.48</td>
<td>0.50</td>
<td>0.25</td>
</tr>
<tr>
<td>envy</td>
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<td>[553, 799]</td>
<td>[0.023, 0.030]</td>
<td>[0.90, 0.97]</td>
<td>[0.37, 0.59]</td>
<td>[0.39, 0.61]</td>
<td>[0.18, 0.33]</td>
</tr>
<tr>
<td>Food + GDA label</td>
<td>0.00036</td>
<td>791</td>
<td>0.020</td>
<td>0.81</td>
<td>0.47</td>
<td>0.50</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>[0.00030, 0.00042]</td>
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<td>[0.018, 0.022]</td>
<td>[0.77, 0.85]</td>
<td>[0.41, 0.54]</td>
<td>[0.44, 0.55]</td>
<td>[0.26, 0.36]</td>
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<tr>
<td>Food + TL label</td>
<td>0.00038</td>
<td>839</td>
<td>0.021</td>
<td>0.74</td>
<td>0.48</td>
<td>0.53</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
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<td>[710, 968]</td>
<td>[0.019, 0.023]</td>
<td>[0.70, 0.79]</td>
<td>[0.41, 0.54]</td>
<td>[0.48, 0.57]</td>
<td>[0.27, 0.36]</td>
</tr>
<tr>
<td>Clothing + Brand</td>
<td>0.00073</td>
<td>512</td>
<td>0.030</td>
<td>0.71</td>
<td>0.41</td>
<td>0.61</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
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<td>[476, 548]</td>
<td>[0.028, 0.032]</td>
<td>[0.66, 0.76]</td>
<td>[0.31, 0.51]</td>
<td>[0.31, 0.65]</td>
<td>[0.16, 0.28]</td>
</tr>
</tbody>
</table>

Note. $\omega$ represents the attribute weight on the top versus the bottom row in the food gamble and the money gamble task; self versus others in the dictator game; taste versus nutrition in the food + nutrition task; clothing appearance versus brand in the clothing + brand task
Additionally, we looked at the goodness of fit between the model with $\omega$ and the model without $\omega$. We evaluated the models based on Watanabe-Akaike information criteria (WAIC; Vehtari et al., 2017; Watanabe, 2010), which is based on the posterior distribution rather than a point estimate (Gelman et al., 2014). We aggregated WAICs from each subject in each dataset and compared differences in these aggregate WAICs between models ($\Delta$WAIC; Fig. 3a). We also checked which model was fit best by the majority of the subjects.

According to summed WAICs, the model without $\omega$ outperformed the model with $\omega$ in the food gamble and the money gamble task (Food gamble: $\Delta$WAIC = -31.7; Money gamble: $\Delta$WAIC= -30.2). In contrast, the model with $\omega$ fit the data better in the other tasks (dictator game (compassion): $\Delta$WAIC= 47.6; dictator game (envy): $\Delta$WAIC= 545.1; food + GDA label: $\Delta$WAIC= 630; food + TL label: $\Delta$WAIC= 367.5; clothing + brand: $\Delta$WAIC= 68.3). The individual WAICs were consistent with the aggregate WAICs: in all cases the majority of subjects were better described by the preferred model at the group level (see Table S6).

Interestingly, in the dictator game, 9 out of 20 subjects in the compassion condition were better described by the model without $\omega$. Meanwhile, all subjects in the envy condition were better described by the full model (see Figure S7).

These results indicate that when the attributes were symmetric (i.e., 50-50 gambles), the attribute weights were determined by gaze. In the other tasks, additional attribute weights needed to be included.

**Attentional discounts**

We next turn to the attentional parameters in the models. For the food and money gamble tasks we used the model without $\omega$, while for the other tasks we used the full model.
We began by comparing group-level attentional parameters in the unrestricted model (Table 2). This comparison revealed that across tasks, $\gamma$ had the smallest value ($M = 0.31$), $\phi$ had the largest value ($M = 0.56$), and $\theta$ was in the middle ($M = 0.44$). In other words, diagonal elements were discounted the most and within-option attributes were discounted the least. This ordering was consistent in every dataset except the money gamble task, where $\gamma$ ($M = 0.46, SD = 0.29$) was slightly higher, but very close to $\theta$ ($M = 0.41, SD = 0.28$). Also, in the food + nutrition tasks, $\phi$ (GDA: $M = 0.50, SD = 0.19$; TL: $M = 0.53, SD = 0.48$) was quite close to $\theta$ (GDA: $M = 0.48, SD = 0.23$; TL: $M = 0.47, SD = 0.23$). Note that, across all tasks and subjects, $\gamma$ ($M = 0.31$), was reasonably close to $\theta \phi$ ($M = 0.25$).
A DYNAMIC COMPUTATIONAL MODEL OF GAZE AND CHOICE

Figure 3. Model comparisons. a). WAIC differences between the model with an additional attribute weight $\omega$ parameter and the model without that parameter. b). WAIC differences between the unrestricted attentional model where the diagonal element gets a discount $\gamma$, and nested models where $\gamma = \theta \phi$, $\gamma = \theta$, and $\gamma = \phi$. In the clothing + brand task, $\Delta$WAIC = 357.52 when $\gamma = \phi$.

We also examined these relationships at the individual level (Fig. 4). The option-wise parameter ($\theta$) was lower than the attribute-wise parameter ($\phi$) for most subjects, in every task but one (food gamble: 83%; money gamble: 76%; dictator game (compassion): 60%; dictator
game (envy): 55%; food + GDA label: 48%; food + TL label: 65%; clothing + brand: 64%). Similarly, the diagonal parameter (γ) was lower than the option-wise parameter (θ) for most subjects, in every task but one (food gamble: 67%; money gamble: 31%; dictator game (compassion): 70%; dictator game (envy): 90%; food + GDA label: 77%; food + TL label: 71%; clothing + brand: 75%).

To more carefully test the hypothesis that γ = θφ, we compared the goodness-of-fit of the unrestricted model with nested models where γ = θ (the non-fixated option gets a fixed discount), γ = φ (the non-fixated attribute gets a fixed discount), or γ = φθ (double discount). Similar to the earlier approach, we used the aggregated WAICs to compare model fits (Fig. 3b).

![Figure 4](image)

**Figure 4. Comparisons of within-individual attentional discounts.** θ − φ represents the difference between the option-wise discount factor and the attribute-wise discount factor; θ − γ represents the difference between the option-wise discount factor and the diagonal discount factor. The black horizontal lines indicate the median values and rectangles indicate the interquartile ranges. The bars represent the lowest/highest value excluding outliers, and the dots represent outliers that are outside 1.5 times the interquartile range above the upper/lower quartiles.

The model with γ = θφ was the best-fitting model in nearly every task. It fit the data better than the model with γ = φ in all tasks, and fit the data better than the model with γ = θ and γ unrestricted, except in the money gamble task. In the money gamble task, the model where γ = θ was the best model (ΔWAIC= -8.2 relative to the unrestricted model). The
aggregated WAICs results also persist at the individual level; most subjects were best described by the double-discount model (except the food gamble task, see Tables S6 & S7).

In sum, we found that the nested model where $\gamma = \theta \phi$ performed better than the other models in six out of the seven datasets. The diagonal element was generally discounted the most, followed by the non-fixated option (within attribute), and then the non-fixated attribute (within option).

**Model predictions**

The DDM predicts basic relationships between attribute value differences and choice probability (Fig. 5) or RT (Fig. 6). The aDDM extension additionally predicts that more gaze to Option X vs. Option Y leads to a higher choice probability for Option X. This means that the duration of individual dwells (Fig. 7), the total relative dwell time (Fig. 8), and the location of the final dwell (Fig. 9) are all predictive of choice. Finally, the maaDDM extension further predicts that more gaze to Attribute A vs. Attribute B leads to more weight on Attribute A (Fig. 10) and that options that have high value attributes that attract the most gaze will be chosen most often (Fig. 11). We found that our best-fitting models provided quantitatively accurate predictions of these relationships in each task (Figs. 5-11).

It is important to note that when simulating the maaDDM for Figures 5-11 we used the actual model with dynamic drift rates rather than the static-drift-rate approximation from the model fitting. This is important because the single-drift-rate approximation cannot capture dwell-level effects (Figs. 7 & 9) because the drift rate is assumed to be constant over the whole trial. Value difference in the food and money gamble tasks were calculated as the difference between the overall left value minus the overall right value after rescaling each element’s value
to 1-10. In contrast, utility differences in the other tasks were calculated after additionally accounting for the attribute weighting at the subject level.

There was one noticeable misfit of the model. This occurred in the envy trials of the dictator game. In this task, there is very little reason to choose the pro-social option. The selfish option earns the decision-maker more money and also reduces inequality. Consequently, subjects choose the selfish option in most cases (85%). Therefore, there is reason to believe that behavior in these trials may obey a simpler non-maDDM choice process.

Figure 5. Choice as a function of value/utility difference. In each plot the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands.
Figure 6. **RT as a function of value/utility difference.** In each plot, the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands.

Figure 7. **Relationship between the duration of the first dwell of each trial and the probability of choosing that first seen option.** In each plot the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands.
Figure 8. Choice as a function of option-level gaze difference. In each plot the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands.

Figure 9. Choice as a function of value/utility differences between the two options, split by the location of the last dwell. In each plot the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands. Value differences were calculated by the overall left value minus the overall right value; Utility differences were calculated by the overall left weighted value minus the overall right weighted value by adjusting the $\omega$ parameter estimated from the best fitted models.
Figure 10. **Choice as a function of attribute-level gaze difference.** In each plot the points represent data with standard error bars clustered by participant, while the dashed/dotted lines represent simulations of the best-fitting models. (a) Food gamble, (b) Money gamble, (c) Dictator games, (d) Food + nutrition labels, (e) Clothing + brands.

Figure 11. **Differences in the model predictions.** To illustrate the difference between the different model specifications, we simulated choice and response time data for the models where $\gamma = \theta \phi$, $\gamma = \theta$, and $\gamma = \phi$ using the Clothing + Brand dataset. We compared the left choice proportion in four different cases, depending on which side had the better brand and which side received more of the brand-focused gaze: (Top left) The left option had the higher value brand and had the higher brand gaze proportion (HvHg); (Top right) The left option had the higher value brand and had the lower brand gaze proportion (HvLg); (Bottom left) The left option had the lower value brand and had the higher brand gaze proportion (LvHg); (Bottom right) The left option had the lower value brand and had the lower brand gaze proportion (LvLg). The simulated parameter values were: $d = 0.0007$, $t_{er} = 512$, $\sigma = 0.03$, $\omega^* = 0.7$, $\theta = 0.4$, and $\phi = 0.6$. 
To test this idea, we ran the following nested model where we set $\phi = 1$:

$$v(\text{gaze at } X_A)_t = v_{t-1} + d[\omega(X_A - \theta Y_A) + (1 - \omega)(X_B - \theta Y_B)].$$

This model assumes that attribute gaze does not bias choices. We then compared this model with the best attentional models from before. The best attentional models outperformed the models with $\phi = 1$ in all the datasets except for the dictator games ($\Delta$WAIC = WAIC (best attentional model) – WAIC($\phi = 1$); food gamble: $\Delta$WAIC = -56.3; money gamble: $\Delta$WAIC = -86.3; dictator game (compassion): $\Delta$WAIC = 55.4; dictator game (envy): $\Delta$WAIC = 387.5; food + GDA label: $\Delta$WAIC = -130.2; food + TL label: $\Delta$WAIC = -85.2; clothing + brand: $\Delta$WAIC = -20.9).

In contrast, we also ran models where we assumed that option gaze does not bias choice ($\theta = 1$). Similarly, we compared this model with the best attentional models from before. The best attentional models outperformed the models with $\theta = 1$ in all the datasets ($\Delta$WAIC = WAIC (best attentional model) – WAIC($\theta = 1$); food gamble: $\Delta$WAIC = -1051.1; money gamble: $\Delta$WAIC = -1403.9; dictator game (compassion): $\Delta$WAIC = -174.5; dictator game (envy): $\Delta$WAIC = -181.6; food + GDA label: $\Delta$WAIC = -607.0; food + TL label: $\Delta$WAIC = -486.2; clothing + brand: $\Delta$WAIC = -1741.5).

In addition, we compared the $\theta = 1$ models with the models where $\phi = 1$. Option-level gaze was more important than attribute-level gaze in every dataset ($\Delta$WAIC = WAIC ($\phi = 1$) – WAIC($\theta = 1$); food gamble: $\Delta$WAIC = -994.6; money gamble: $\Delta$WAIC = -1317.7; dictator game (compassion): $\Delta$WAIC = -230.0; dictator game (envy): $\Delta$WAIC = -569.1; food + GDA label: $\Delta$WAIC = -476.8; food + TL label: $\Delta$WAIC = -401.1; clothing + brand: $\Delta$WAIC = -1720.5).

**Decision Field Theory predictions**
Earlier, we found that gaze to attributes predicted the weight on those attributes in subjects’ choices. Our model accounts for this effect through the parameter \( \phi \) (and \( \gamma \)), which discounts the impact of the unfixated attribute. However, we can also ask whether subjects allocate more gaze to more important attributes, after accounting for the \( \phi \) (and \( \gamma \)) effects. In other words, we can test whether there is a correlation between gaze proportion to Attribute A and the parameter \( \omega \), which is estimated while controlling for the attentional discount parameters.

![Figure 12. Relationship between attribute importance and attribute gaze.](image)

There was no difference in attribute importance in food and money gamble tasks because the attributes were symmetric in those tasks. In the other tasks, we found that more gaze was sometimes allocated to the higher weighted attribute (Fig. 12): (dictator game (compassion): \( r = \))
0.46, \( p = 0.041 \); dictator game (envy): \( r = 0.041, \ p = 0.87 \); food + GDA label: \( r = 0.23, \ p = 0.11 \); food + TL label: \( r = 0.51, \ p < 0.01 \); clothing + brand: \( r = 0.14, \ p = 0.49 \).

**Exploratory analysis of gaze transition patterns**

In addition to the analyses in the previous section, we can also investigate gaze transitions between attributes and alternatives. While the transitions themselves are not a part of the maaDDM, they may indirectly affect choice outcomes through their effects on gaze allocation.

We find a fair amount of heterogeneity across tasks in terms of the relative proportion of within-attribute and within-alternative transitions (Fig. 13). We find that in the symmetric food gamble and money gamble tasks, subjects exhibited more within-alternative transitions than within-attribute transitions. On the other hand, in the non-symmetric food + nutrition label and clothing + brand tasks, subjects exhibited more within-attribute transitions than within-alternative transitions. The dictator games fell in between, with roughly equal numbers of within-option and within-attribute transitions. In all tasks, diagonal transitions were extremely rare.

To better quantify these relative transition patterns, we calculated the Payne Index for each task (Fig. 14). The Payne Index represents the relative number of within-alternative transitions relative to the number of within-attribute transitions (Payne et al., 1988). We found significantly positive Payne Indices for the food gamble (\( p < 10^{-16} \)) and money gamble (\( p < 10^{-16} \)) tasks, and significantly negative Payne Indices for the food + nutrition (TL & GDA: \( p < 10^{-16} \)) and clothing + brand (\( p < 10^{-16} \)) tasks. The Payne Index for compassion trials was not
significantly different from zero (p=0.22) while the envy trials were significantly negative (p < 10^{-7}).

![Gaze transitions patterns.](image)

**Figure 13. Gaze transitions patterns.** The y-axis represents the average number of transitions per decision, across participants. The error bars represent standard error bars clustered by participants. Within-alternative transition represents transitions between attributes that belong to the same option. Within-attribute transition represents transitions between options on the same attribute. Diagonal transition represents transitions from one attribute of one option to the other attribute of the other option.

Finally, we examined whether there is a relationship between the Payne Index and the weight on the more important attribute $\omega$. Pooling subjects across tasks, we indeed found a strong negative relationship between $\omega$ and the Payne Index ($r = -0.53$, p < 10^{-16}, Fig. 15). This means that subjects who put more equal weights on the attributes exhibited more within-alternative transitions.
Figure 14. **Mean Payne Index for each task.** Payne Index is calculated based on the number of within attribute transitions and the number of within alternative transitions as follows: 

\[
\frac{\text{#. within alternative} - \text{#. within attribute}}{\text{#. within alternative} + \text{#. within attribute}}
\]

A score of 1 represents a fully alternative-based search (most transitions within alternative) whereas a score of -1.0 represents a fully attribute-based search (most transitions within attribute). Error bars are standard errors clustered by participant.

Figure 15. **The correlation between the Payne Index and the weight on the more important attribute.** Each dot represents a single subject and different colors are from different tasks.
Discussion

In this work, we investigated the relationship between overt attention and choice at both the option and attribute level, by introducing a multi-attribute attentional drift diffusion model (maaDDM) and then testing variants of the model with different assumptions about attentional discounts and attribute weights. The results highlight the distinct roles of gaze bias at the option and attribute levels. In particular, we find that non-fixated options are consistently discounted to a greater extent than non-fixated attributes, while the non-fixated attribute of the non-fixated option is discounted most.

Accounting for the effects of gaze on choice is important because a large body of research has shown that gaze to options correlates with choosing those options (Krajbich, 2019). Here we have seen that gaze to different attributes of options is also linked to choices, consistent with other recent work (Amasino et al., 2019; Reeck et al., 2017; Rramani et al., 2020; Westbrook et al., 2020). Our maaDDM provides a quantitative account of both phenomena by modeling drift rate as a function of attribute values and gaze location.

It is important to note that while we assume the eye-mind hypothesis that gaze indicates the center of attention (Just & Carpenter, 1980), we also acknowledge that gaze and attention are not the same thing. The fact that $\theta>0$ and $\phi>0$ indicates that people are able to attend to options and attributes that they are not looking at, consistent with the literature on covert attention (Carrasco & McElree 2001). Moreover, the (ma)DDM is a model linking gaze and drift rate and so is agnostic about the direction of causality between them. It could be that shifts in gaze lead to shifts in attention and thus drift rate, or it could be that attention and drift rate shift first, followed by a shift in gaze.
That being said, a related line of the research has studied the causality between gaze and choice, and has shown that choice biases can arise from exogenous gaze manipulations (Armel et al., 2008; Ghaffari & Fiedler, 2018; Gwinn et al., 2019; Kunar et al., 2017; Lim et al., 2011; Pärnamets et al., 2015; Tavares et al., 2017; Towal et al., 2013), but see and Newell & Le Pelley, 2018. In the realm of multi-attribute choice, manipulations of information acquisition have also been shown to change behavior (Reeck et al., 2017). One recent article argues that there is insufficient evidence for this causal link (Mormann & Russo, 2021), but that article overlooks several of the examples referenced above and in the one counterexample that they cite it is unclear whether attention was successfully manipulated during the choice process, which is when the aDDM operates (Glaholt & Reingold, 2009).

There is a related question of what kinds of information gaze modulates, assuming it does. Most work with the aDDM has relied on choice tasks using rich visual stimuli such as images of snack foods (Ashby et al., 2016; Fisher, 2017; Krajbich et al., 2010), durable consumer goods (Krajbich et al., 2012), artwork (Vaidya & Fellows, 2015) and tilted lines (Tavares et al., 2017), This work suggests that gaze might dictate the rate of information extraction from visual stimuli. However, other work has studied the role of memory in value-based decisions. Some of this research has argued that these decisions are based on memories or thoughts evoked by the stimuli (e.g., Bakkour et al., 2019; Pärnamets et al., 2015; Shadlen & Shohamy, 2016). Another recent article used a task with decisions based purely on memory and found an even stronger link between gaze and choice than when the stimuli were present (Weilbächer et al., 2021). Finally, Smith & Krajbich (2021) compare stimulus-based and memory-based decisions within the aDDM framework and find many similarities between the
two contexts. Together, these findings suggest that gaze relates to what information is being externally or internally retrieved.

Our work provides the basis for a general model of multi-alternative, multi-attribute choice. In this way, our model is an advance beyond past work, which has either focused on single-option choice (Fisher, 2017; Krajbich et al., 2012) or on particular choice domains (Amasino et al. 2019; Glickman et al. 2019). Recent efforts have emphasized the importance of integrating different psychological theories into general models of decision making (Erev et al., 2017; He et al., 2020; Peterson et al., 2021). Here, by developing the maaDDM for multi-attribute choice, we present a theoretical integration of two earlier lines of sequential sampling models (aDDM and Decision Field Theory). Moreover, the model can be easily extended to more than two attributes or options by simply applying the attribute gaze discount factor $\phi$ to all non-fixated attribute values and the option gaze discount factor $\theta$ to all non-fixated option values in the drift rate calculations, as in Krajbich & Rangel (2011) or Thomas et al. (2021).

Empirically, the principles of this simple extension might be more complicated as some attributes/options may be physically and semantically closer to another (Kleinmuntz & Schkade, 2016; McClelland & Rumelhart, 1981; Trueblood et al., 2014), or options may share the same attributes (e.g., Bhatia, 2017). However, the maaDDM provides a framework for investigating these questions and building more complex, nuanced models.

Our results are consistent with Krajbich et al. (2012) and Fisher (2017) in demonstrating smaller attribute-level than option-level gaze effects on choice. This suggests that it may be easier to construct an option from a set of attributes than to compare different options (Glickman et al. 2019). That observation is consistent with past work showing that patients with damage to the reward/choice network (namely the ventromedial prefrontal cortex) seem to avoid
comparisons and instead favor within-option evaluations (Fellows, 2006). However, this does raise the question of why neurotypical subjects often prefer within-attribute comparisons (Amasino et al., 2019; Fellows, 2006; Reeck et al., 2017). One possible hint comes from our analysis of gaze transition patterns. We find primarily within-option transitions when there are similar weights on the two attributes, but more within-attribute transitions when the attributes differ in importance (Fig. 13). Thus, one factor that seems to affect transition patterns is the nature of the attributes.

Our finding regarding the non-fixated attribute of the non-fixated option aligns with the notion that attention is a gradient, affecting some elements more than others (McGinty et al., 2016). If the non-fixated option receives an attentional discount and the non-fixated attribute receives an attentional discount, then it stands to reason that the diagonal element might receive both discounts. This is indeed what we found in all but one dataset. It is worth noting that this “diagonal” element was farthest from the center of attention, both mentally and spatially. It thus remains to be seen whether the spatial layout of the elements affects these results.

The one exception to the diagonal finding was in the money gamble task, where the entire non-fixated option received the same discount. This may indicate that people find it easy to mentally combine cash outcomes, possibly as an expected-value calculation (Arieli et al. 2011). That would be consistent with prior research indicating that within-gamble integration is more frequent than across-gamble comparison (Fiedler & Glöckner, 2012; Glöckner & Betsch, 2008).

Surprisingly, the gaze discount rates do not appear to be consistent within an individual. Subjects who discounted the diagonal element more heavily than the horizontal element did not necessarily discount the horizontal element more heavily than the vertical element. Recent work has examined the individual-level link between option-level gaze and choice, with considerable
differences across individuals (Smith & Krajbich, 2018; Thomas et al., 2019). Our results indicate that different factors must at least be partially contributing to option-level and attribute-level discount rates.

Our findings are also consistent with research that suggests information enters the decision process sequentially (Amasino et al., 2019; Diederich, 1997; Diederich & Oswald, 2014; Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; Maier et al., 2020; Sullivan et al., 2015; Teoh et al., 2020). As gaze shifts to a new piece of information, it may appear as though that information is suddenly entering the decision process. In reality, it may simply be amplified by being the focus of attention.

This work enhances our understanding of attribute weighting and attribute gaze. Gaze allocation reflects attribute weighting, with more gaze to more important attributes. This confirms previous eye-tracking results (e.g., Fiedler & Glöckner, 2012), and assumptions in Decision Field Theory (Diederich, 1997). However, some researchers have suggested a more complex relationship between attribute properties and attention. Bhatia (2017) finds that common attributes and distinct attributes receive a roughly equal amount of attention. In contrast, evidence from Sütterlin et al. (2008) highlights that attractive and unattractive features receive more attention than common features. In any case, it is clear from our findings, and from prior research (Krajbich & Rangel, 2011; Towal et al. 2013; Gluth et al. 2020; Thomas et al. 2021; Mormann & Russo 2021) that gaze is not random when there are multiple attributes or more than two options. How gaze is allocated during decision making is an important question going forwards, and there are already several articles examining the problem in simple settings (Callaway et al., 2021; Jang et al., 2021; Li & Ma, 2021; Song et al., 2019). The goal of the current paper was to understand the relationship between gaze and choice. By doing so, we
sidestepped modelling the gaze process. In the future, when gaze models are developed, they could be used as inputs to our choice model. Thus, future work should focus on multi-attribute extensions of these simpler gaze models.

It is worth mentioning that the influence of gaze on attribute weights may not be as simple as we have assumed in the model. Other features of the gaze patterns, such as transitions or refixations may also affect the decision process (Russo & Dosher, 1983; Russo & Rosen, 1975). The ability to extract information from the stimuli (e.g. fluency or attitude accessibility) may also impact the extent to which gaze amplifies the information (Oppenheimer, 2008; Gwinn & Krajbich 2020), as we observed in the food + nutrition label tasks (Rramani et al. 2020). With this simple model, gaze is not sufficient to account for subjects’ attribute weights. Thus, the model requires additional attribute-weight parameters. More work is needed to see if that can be avoided with more complex modeling of the gaze data.

It is also worth noting that when fitting the model to the data, we approximated the dynamic multi-stage drift rate with a single static drift rate by using gaze-weighted attribute values. This approach has been used in other related work (Cavanagh et al., 2014; Smith et al., 2019; Thomas et al., 2019, 2021). However, we acknowledge that this approximation is not representative of the actual choice process and is just a method to facilitate model fitting. For example, drift rates will change within a trial due to gaze shifts, and those changes will also differ across trials with the same average drift rate, based on the particular values of the attributes. By ignoring these sources of variance, the approximation is unable to capture some aspects of the data (see also Rieskamp (2008)). The question is whether the approximation biases or distorts the model fits. Based on our parameter recovery exercises we have no reason to believe that it does (Fig. S5 & S10). Nevertheless, in the future it may be worth pursuing
alternative fitting methods to assess if the approximation results in any biases (Diederich & Busemeyer, 2003; Diederich & Oswald, 2014; Li & Ma, 2021; Srivastava et al., 2017). It is worth noting again that all of the model simulations presented in the figures use the actual maaDDM and not the approximation used in the fits. Therefore, the model itself does account for the dynamic aspects of the drift rate, which is why it can explain things like the last fixation effect. The linear approximation is only used in estimating the best-fitting parameters. Once those parameters are identified, the comparisons between the data and model are done using the full, dynamic model.

Another aspect of the modeling that requires more investigation is the value scale. Here, we assumed all attribute values were positive and placed them on the same 1 to 10 scale. This is not a trivial step. Depending on the study and attribute, these values were based on ordinal rankings (clothing brands), objective information (health scores; cash outcomes), or subjective value ratings. Moreover, one study used a subjective value scale ranging from “not at all” to “very much” (food + labels task), one study used a scale ranging from “very disliked” to “very liked” but excluded all disliked items (food gamble task), and one study used a scale ranging from “really dislike” to “really like” and used all items (clothing + brand task). By rescaling all these attributes from 1 to 10 we are implicitly assuming that the lowest-rated attribute values in each task/attribute are roughly neutral. This seems like a reasonable assumption in most cases, though one might question it with the health scores and clothing ratings. With respect to the food + labels task, every trial involved an unhealthy item, so if we excluded unhealthy items, there would have been no data left. With respect to the clothing + brand task, it seems unlikely that subjects actually found the items aversive, only not appealing.
The reason that the value scale matters is that the aDDM (and the maaDDM by extension) has a multiplicative interaction between gaze and value. This means that positive/attractive information benefits from more gaze, while negative/aversive information suffers from more gaze (Armel et al., 2008; Smith & Krajbich, 2018). Thus, it is important to properly locate the values of the items, not just relative to each other, but also relative to neutrality, i.e. value = 0. Analyzing the nutrition labels and clothing brands, we found a strong positive relationship between choice probability and the differences in dwell time in both datasets (see Supplementary Note 3), suggesting that the items were viewed positively.

The maaDDM may be helpful in addressing context effects in the multi-attribute multi-alternative preferential choice literature (Huber et al., 1982; Simonson, 1989; Tversky, 1972). Context effects occur when the addition of a third option distorts a decision maker’s preference between two existing options. Context effects are thought to arise from a combination of sequential sampling model dynamics and attentional shifts between options and attributes (Berkowitsch et al., 2014; Noguchi & Stewart, 2014; Roe et al., 2001). These effects have been found not only in consumer choice, but also in perceptual choices (Lea & Ryan, 2015; Molloy et al., 2019; Trueblood et al., 2014). The maaDDM may provide a framework to quantitatively model these effects, with some additional modifications. First, decoys may increase attention to the target option. In the attraction effect, the dominated option may prompt comparisons with the nearby, dominant target. This is consistent with Noguchi & Stewart, 2014 and Molter et al., 2021. In the similarity effect, attention to the decoy may spillover to the target (and vice versa) preventing either option from standing out. In the compromise effect, the centrality of the compromise option may attract attention, consistent with Molter et al., 2021. Second, decoys may increase the perceived importance of the “worse” attribute (e.g. by increasing the variance of that attribute) leading to a
more balanced weighting of the attributes, which could favor the compromise. This is somewhat consistent with results from Noguchi & Stewart (2014) showing attribute-and-alternative-wise comparisons. We do acknowledge that the maaDDM by itself cannot completely account for the context effects, since it is agnostic about the patterns of gaze; it only provides choice predictions as a function of gaze. Therefore, more modeling of the gaze process (and other cognitive mechanisms like fluency) will be needed to attempt to fully understand the context effects (Bhatia, 2013; Busemeyer et al., 2019; Cohen et al., 2017; Gluth et al., 2018).

We do acknowledge that the maaDDM may not always be an appropriate model for a given task. For instance, in the present article, we found that the maaDDM did not provide a good account for the “envy” task where subjects were overwhelmingly selfish and so presumably were just looking for the larger payoff for themselves. Other work on reinforcement learning has found that model-free, but not model-based, subjects are well explained by the aDDM (Konovalov & Krajbich, 2016). On the other hand, contrary to some recent claims (Mormann & Russo, 2021), our current findings indicate that the maaDDM framework can do a good job of capturing decisions involving more than one dimension, which require more deliberation and computation of subjective values. However, we cannot yet say whether the maaDDM will be as good at capturing behavior with more complex decisions, such as those studied in Russo & Dosher, 1983; Russo & Leclerc, 1994; Russo & Rosen, 1975.

In conclusion, the model presented in this article provides a framework to account for the relationships between value, gaze, choice, and response time in decisions involving more than a single attribute, and the empirical evidence supports the model in cases with two options and two attributes. It serves to further cement the bridge between cognitive psychology and JDM/behavioral economics. This perspective is crucial to understanding the dynamics of the
decision process, allowing us to decompose decisions into cognitive components, to relate them to process-tracing and neuroscience data (Hunt et al., 2014), and to ultimately better predict choice behavior.

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