Attention and Choice Across Domains
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Introduction

Among the decisions people make on a daily basis are choices from several different domains. For instance, consider a familiar and relatively innocuous scenario: a visit to a coffee shop. In this situation, there are multiple decisions to be made. People must decide which beverage to order. They also decide whether or not to leave money in the tip jar as they grab their coffee. At first, these two decisions might seem to be driven by entirely different mechanisms. However, is there really such an insurmountable difference between them? That is, does domain matter? Is the choice process for selecting which food to eat any different from the one invoked when deciding which lottery ticket to purchase? In this paper, we contend that regardless of the domain in which a decision is made, the underlying choice process is the same.

According to current theory, the decision-making process can be understood (and subsequently modeled) as a course of evidence accumulation. There are a variety of different model manifestations of the decision making process that can adequately account for choice and response time (RT) data (Bogacz, 2007; Ratcliff & Smith, 2004; Busemeyer & Diederich, 2002). In the current paper, we will focus on the drift diffusion model (DDM; Ratcliff, 1978) and its extensions (Krajbich et al., 2010), which have several key properties. For instance, as people consider the alternatives in the choice set, they noisily gather evidence about each of the alternatives. Once enough positive evidence is gathered for one option (relative to the other), the person chooses it. Because the evidence accumulation is relative, evidence in favor of one alternative is naturally evidence against the other.

In our value-based choice study, we conceptualize the evidence accumulation process using an extension of the DDM: the attentional drift diffusion model (aDDM), first developed by
Krajbich et al. (2010). The aDDM enables us to capture the effects of attention\(^1\) on choice by adding an attentional discounting parameter to address the effects of attention on evidence accumulation – and subsequently, on choice. Attention to one alternative results in a discounting of the non-fixated option’s value and thus, the rate of evidence accumulated for that alternative throughout the duration of the fixation (Figure 1).

Past research into the effects of attention on decision making has explored choices in a variety of domains, including consumer goods (Krajbich et al., 2010; Krajbich, Lu, Camerer, & Rangel, 2012), risky gambles (Fiedler & Glöckner, 2012; Stewart, Hermens, & Matthews, 2015), and social proclivity (Fiedler, Glöckner, Nicklisch, & Dickert, 2013). This body of research supports an important link between attention and choice, namely, that attention to one alternative increases the likelihood of choosing that option.

Despite the consistencies observed in multiple contexts, all of the previous studies have each explored only one domain in isolation. Thus, even though many results regarding the decision-making process have been replicated in more than one context, all of these comparisons have been across entirely separate groups of participants. In the current study, we have used a within-subjects, multi-domain design in order to definitively establish the existence of an attentional mechanism that transcends decision domains.

**Method**

Forty-four university students participated in this study. Of these, 34 completed all of the tasks in the study.

Stimuli were presented using the MATLAB (Mathworks, 2014) Psychophysics Toolbox (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). An EyeLink 1000 Plus was used to collect

\(^1\) In this study, “attention” refers to external attention of the visual modality, measured by eye movements toward and extended fixations upon on-screen stimuli (see Chun, Golomb, & Turk-
eye-tracking data. Attentional regions of interest (ROIs) were defined a priori, each containing one of the stimuli on the screen. Participants indicated all of their responses with button presses using a standard keyboard.

In the first task, participants rated their desire to eat each of 147 snack food items (chocolate, candy, chips, etc.) on a discrete scale from -10 to 10. Participants were told that a rating of -10 should be used indicate an extreme dislike of the item, a rating of 10 should be used to indicate an extreme liking of the item, and a rating of 0 should be used to indicate neither liking nor disliking the item (Figure 2). Participants used the keyboard left/right arrow keys to move an on-screen indicator along the spectrum to the appropriate rating. Only positively-rated food items were used in subsequent tasks; choice sets did not contain any aversive items. Participants were allowed as much time as they desired to complete this task.

Participants were then calibrated to the eye tracker and their eye movements were tracked for the remainder of the study. Next, each participant completed four core choice tasks: two-food, four-food, risk, and social (Figure 3) in a blocked design, by task. Each core task comprised 200 trials and these binary choice tasks were presented in a random order across participants. In all four core choice tasks, participants selected the left option by pressing the “F” key and the right option by pressing the “J” key on the keyboard. Additionally, there was no time pressure in any of the choice tasks; participants took as much time as they wished to respond to each decision. In between trials, participants were presented with a fixation cross in the center of

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2 Some participants did not have enough positively-rated food items to generate 200 trials in the subsequent food choice tasks, subject to constraints on the number of times a food item could be presented (7) and the maximum difference in rating between the left and right options: five in two-food, four (expected value) in four-food. These participants completed as many constraint-satisfying trials as could be generated.
the screen. Participants automatically progressed to the next trial only after they had fixated on the cross for one second.³

In the two-food task, a replication of Krajbich et al. (2010), participants were presented with two previously-rated food items, one on each side of the computer screen, and asked to choose the one they would like to eat most at the end of the experiment. In the four-food task, participants saw four food items, one in each quadrant of the screen. Each option (left and right) represented a 50/50 gamble between the two items on that side of the screen. Thus, if the participant chose the left option, he was selecting a lottery between the top left and bottom left food items.

The risk task was similar to the four-food choices in that each option consisted of an even-probability (i.e. 50/50) gamble. However, instead of food items, the choices were monetary, represented by four squares, one in each quadrant of the screen. Specifically, the white proportion of each square directly corresponded to an amount of money, ranging from $0-10 (participants were informed of this structure). In each decision, there was an inherent tradeoff between selecting a safer (i.e. less variable) option and a riskier option (i.e. with higher maximum payoff but also higher variability). Partially-filled squares were used to prevent participants from doing explicit expected value calculations. All participants saw the same 200 gambles in a randomly presented order. Additionally, each gamble was randomly presented both across options (left vs. right) and within an option (top vs. bottom). That is, the amounts within each alternative could be presented in the top or bottom row and the two alternatives could, in turn, be presented on either side of the screen.

³ If the participant ever required re-calibration to the eye-tracker, this one-second inter-trial fixation check made the requirement obvious.
The social task used the same square paradigm as the risk task to represent amounts of money. However, in this choice domain, each option consisted of a payoff for the participant (self: a square with red fill) and a payoff for the next participant (other: a square with blue fill). As in the risk task, the participant faced a tradeoff in each trial between selfishness and prosociality. The selfish option had the higher payoff (compared to the pro-social option) for the current participant, whereas the pro-social option had a higher payoff (compared to the selfish option), for the next participant. Colors (red/blue) were held constant across participants, but the row in which the payoffs (self/other) appeared were counterbalanced across participants.

Each of the choice tasks was incentivized; one randomly-selected trial from each of the domains (food, risk, and social) was selected and the payoff was realized for the participant at the end of the study. For the tasks that involved a gamble over the potential outcomes (i.e. four-food and risk), a trial was selected; from that trial, one of the outcomes within the chosen alternative was randomly selected as the result with even probability (exactly as was explained to the participants). The “other” payoff from the randomly-selected social trial was given to the next participant. Participants were not informed of the amount sent to them by the previous participant until after they had completed the entire study.

Results

Unsurprisingly, participants noisily chose in line with their valuations in all of the tasks (Figure 4). For example, in the two-food task, participants increasingly chose the left item as its relative value to the right item increased; they chose the left item ~50% of the time when the items were equally valued. In the four-food and risk tasks, people usually chose in line with the expected values of the two alternatives on each trial. In the social task, people typically chose in line with the “self” payoff within each option.
To account for differences in risk aversion and pro-social tendencies in later analyses, the values in the risk and social choices were reframed using individual-level utility functions. An exponential utility function \( U(x) = x^a \) was fit to each participant for the risk task. On each trial, the likelihood of choosing the left option (with potential outcomes \( V_{UL} \) and \( V_{LL} \)) is assumed to be \[ \exp(\lambda \ast \left[\frac{(V_{UL}^a + V_{LL}^a)}{2} - \frac{(V_{UR}^a + V_{LR}^a)}{2}\right]) \] and the values of alpha and lambda that best fit the observed data according to maximum likelihood (using the optim function, R Core Team, 2015). The corresponding estimates of alpha were used to transform the objective values in each gamble into subjective utilities.

Similarly, using the Charness-Rabin model \( U(x_i, x_j) = (1 - \beta r - \alpha s)x_i + (\beta r + \alpha s)x_j \), each participant’s best-fitting alpha (disadvantageous inequality) and beta (advantageous inequality) parameters were selected according to maximum likelihood\(^4\) (Charness & Rabin, 2002). Because of the arbitrariness of utility magnitude and the variability that exists across individuals, utility values were z-scored within each participant for each task in order to yield a more standardized measure of subjective valuation. The risk and social task results will henceforth be discussed in terms of this standardized utility measure, while the two- and four-food choice findings will continually be interpreted according to the subjective value of the food items, individually provided during the rating task.

As many previous researchers have demonstrated throughout the decades (Busemeyer, 1982, 1985; Busemeyer & Townsend, 1993; Cavanagh, Wiecki, Kochar, & Frank, 2014; Dai & Busemeyer, 2014; Fiedler & Glöckner, 2012; Gluth, Rieskamp, & Büchel, 2012; Hare, Malmaud, & Rangel, 2011; Hunt et al., 2012; Krajbich et al., 2010, 2012; Krajbich, Oud, & Fehr, 2011;...

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\(^4\) Here, \( x_i \) is the “self” payoff, \( x_j \) is the “other” payoff, \( r \) is an indicator for \( x_i > x_j \), and \( s \) is an indicator for \( x_i < x_j \).
2014; Krajbich & Rangel, 2011; Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010; Petrusic & Jamieson, 1978; Philiaistides & Ratcliff, 2013; Polanía, Krajbich, Grueschow, & Ruff, 2014; Stewart et al., 2015; Towal, Mormann, & Koch, 2013), the hardest decisions take the longest to make. In the present study, all four tasks demonstrated an inverse relationship among the value difference between the two options and the response time (RT) of the participant (Figure 5). Intuitively, when two alternatives differ greatly in subjective value, the decision is easier to make, and it takes less time (on average) to make it. However, when the values of the options are very close, it is a harder decision and average RTs are markedly higher. A direct relationship between choice difficulty and RT is indeed the pattern found in this data.

Although this inverse RT-difficulty pattern is consistent across the different tasks, the tasks clearly differ in the speed with which participants take to complete them (Figure 5). The shortest, on average, were the two-food choice decisions ($M = 1.59s$, $SD = 1.73s$). Intuitively, this is to be expected. There are only two (compared to four) stimuli on the screen, so there is less information for the participants to take in. On the other hand, the longest decisions, on average, were those in the four-food choice task ($M = 2.68s$, $SD = 2.41s$). The risk choices ($M = 2.66s$, $SD = 4.70s$) were slightly faster than the four-food decisions, while the social choice RTs ($M = 1.85s$, $SD = 1.78s$) hovered much closer to those of the two-food choice task.

Albeit strange at first glance, this trend can be explained by some significant individual differences. Despite responding to the same 200 decisions, participants differed wildly on the ratio of selfish/pro-social options that they selected. The distribution of selfish choice proportions was relatively bimodal, so we split the participants into two groups accordingly: participants who chose the selfish option on at least 90% of trials were classified as “selfish” (N
= 14), while the rest of the participants were classified as “pro-social” (N = 22). The selfish participants made their choices significantly faster, on average, than the pro-social participants, \( t(27.203) = -4.5832, p < 0.001 \).

As in previous research on the effects of attention on decision making (Arieli, Ben-Ami, & Rubinstein, 2011; Armel, Beaumel, & Rangel, 2008; Ashby & Rakow, 2015; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Fiedler et al., 2013; Krajbich et al., 2010, 2012; Krajbich & Rangel, 2011; Mormann, Navalpakkam, Koch, & Rangel, 2012; Pärnamets et al., 2015; Stewart, Gächter, et al., 2015; Towal et al., 2013), participants’ choices were influenced by their attentional patterns. This influence was remarkably consistent across the domains in the current experiment, as seen in Figure 6. A half-second increase in the amount of time spent looking at the left option (relative to the amount of time spent on the right option) corresponds to roughly a 25% increase in the likelihood of choosing the left option.

Intuitively, it seems that the effect of attention on choices might be explained simply as a tendency to spend more time looking at options that are more appetitive (figuratively and literally). However, the data suggests that attention and value contribute independent effects on choice in so much as attention and subjective valuation are largely uncorrelated (Figure 7). The duration of middle fixations (classified as attention to an ROI that is neither the first nor the last attentional shift observed in a trial) are generally unrelated to the value of the fixated item/amount on the screen. Table 1 outlines the linear regression models for each task, in which

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5 One participant chose the pro-social option in 97.5% of trials. It is possible that this participant misunderstood the directions and mixed up the colors and intended to choose the selfish option in 97.5% of trials. If this participant is excluded (or instead re-coded as selfish), the subsequent results do not change.

6 Middle fixations (as opposed to first or last fixations) are used in this analysis to preserve homogeneity. First and last fixations are significantly shorter than middle fixations, on average,
middle fixation durations are regressed on the fixated item’s (or amount’s) value. After clustering the standard errors to account for individual differences, we see that the subjective value of the fixated item does not typically influence the middle fixation duration.

The risk task surprisingly shows a slight increase in middle fixation duration as the standardized utility of the amount increases. However, this is likely a product of the task design: higher amounts are represented by a larger white area against a black background. Previous research has demonstrated that more salient items receive more attention and that this salience-driven attention contributes to choices (Mormann et al., 2012; Towal et al., 2013). Thus, because the values in the risk task are perfectly correlated with salience, it is possible that the attention-value relationship observed herein is simply the result of additional salience.

Moreover, because the risk task is the only choice domain in which salience and subjective value are entirely conflated, it makes sense that it would, too, be the only domain in which we find a significant relationship between middle fixation duration and the value of the fixated item. Ultimately, these results provide evidence that it is not the case that participants’ attentional patterns are determined by their subjective valuations for the items (and that choices are solely driven by valuation), but instead that attention and valuation individually influence the participants’ choices.

Because attention to an alternative increases the relative rate of evidence accumulated for that option, the last-fixated option is more likely to be chosen, compared to when it is not looked

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7 The social task uses a similar format, but subjective value and salience are only positively correlated within a participant’s own payoffs, which only constitute half of the visual display on each trial. Additionally, the colors of the self and other amounts (red and blue) are less salient than the ultimate brightness/contrast of white on black and thus, are likely to have a smaller influence on attention and subsequent choice (Towal, Mormann, & Koch, 2013).
at. Figure 8 demonstrates this relationship. If, instead, attention to an alternative yielded no advantage in evidence accumulation and the drift rate is consequently equivalent across fixation shifts (i.e. $\theta = 1$), then the direction of the last fixation should not affect choice proportions. In this case, the two choice curves would be indistinguishable and Figure 8 would be identical to Figure 4. However, the clear separation of the left and right fixation curves indicates a non-trivial discounting of the non-fixated option.

Despite this group-level finding, there are drastic individual differences at the participant level in terms of the influence of attention on choices. To operationalize these individual differences, we estimated the following logistic regression model for each participant, for each task:

$$P(\text{Choose Left}) = \beta_0 + \beta_1(VL - VR) + \beta_2(FixL - FixR)$$

In this model, $VL$ and $VR$ correspond to the values of the left and right options, respectively. In the four-food and risk tasks, $VL$ and $VR$ are the expected subjective values of each alternative, based on the food ratings supplied by the participants and the standardized utilities supplied by the fitted exponential utility model. In the social task, $VL$ and $VR$ are standardized utilities from the Charness-Rabin model. Thus, $VL - VR$ is a value difference measure, used here as a covariate to account for the fact that participants tend to choose in line with their valuations (Figure 6). The true coefficient of interest is $\beta_2$, which is attached to the time advantage measure, given by $FixL - FixR$. Here, $FixL$ and $FixR$ refer to the total fixation time for the left and right alternatives on a given trial.

This logistic regression model gives us clear insight into the effects of attention on an individual’s choices in one domain. To determine the consistency of individual-level attentional influence, we computed pairwise correlations between the tasks of the time advantage
coefficients across participants. Strong positive correlations, therefore, indicate that participants who are highly affected by attention in one task are also highly influenced by attention in another (i.e. evidence for cross-domain consistency in the magnitude of the effect of attention on choice). The results of these correlations, across all participants, appear in Table 2. Clearly, there are robust participant-level consistencies among the two-food, four-food, and risk tasks. At first glance, however, the social task appears to be devoid of any meaningful correlation.

However, this insignificance is driven entirely by the selfish participants. When the data are split according to social preference, the selfish participants still demonstrate no correlation between their time advantage coefficients in the social task and the coefficients in the other tasks. The pro-social participants tell a markedly different story. Among these participants, the magnitude of attentional influence on choice is consistent across all domains,\(^8\) including the social task (Table 2). This is a core finding of this research: these correlations demonstrate strong evidence for a consistent individual-level attentional effect on choices across multiple domains, at least for pro-social participants. It provides evidence, therefore, for a domain-general choice process, moderated similarly (within a person) by attention to the alternatives.

**Conclusions**

The results presented here provide substantial support for a domain-general choice process with remarkable consistency at the individual level. Although individuals differ in the extent to which attention influences their choices (as evidenced by the range of logistic regression coefficients in a model of choice regressed on attention), the participants demonstrated reliable choice-attention patterns, suggesting that the method by which we choose between alternatives is consistent across choice contexts.

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\(^8\) The correlation between the two-food and risk task is marginally significant, with \(p = 0.09266\).
Ultimately, the recurring theme in this research is the consistency in the connection between attention and choice. This underlying connectivity has surely been hypothesized, based on the consistent attention-choice link observed in distinct domains in separate studies (with independent participant samples). However, until now, the stability of attentional influence has not been demonstrated within a participant. Therefore, the current study not only adds evidence for an attention-choice link to the growing body of literature, but also verifies the existence of a domain-general decision-making process.

**Figures and Tables**

Figure 1. The attentional drift-diffusion model (aDDM, Krajbich et al., 2010). Attentional shifts (denoted by the green and yellow shaded portions) between the left and right options change the drift rate of the decision process.

Figure 2. Food rating task. Participants rated their desire to eat 147 food items on a scale of -10 to 10. Only positively (1-10) rated items were used in subsequent tasks.
Figure 3. **Core choice tasks.** Participants completed 200 trials of each task in a blocked design. A. Two-food: Participants chose between two food items. B. Four-food: Participants chose one of two 50-50 gambles over two foods (i.e. the left two foods or right). C. Risk: Participants selected one of two 50-50 monetary gambles. The level of white fill corresponds to the amount of money received by the participant. D. Social: Participants chose between two divisions of money between themselves and the next participant. The amount of red fill represents the self-payoff, while the amount of blue fill corresponds to the future participant’s payoff.

Figure 4. **Effect of value difference on choice.** Probability of choosing the left option, based on the subjective value difference between the two alternatives.

Figure 5. **Effect of choice difficulty on response time (RT).** Mean RT across participants as a function of the subjective value difference between the alternatives. More difficult choices (where the two options are closer in value) take longer to make. The bars represent standard errors.
Figure 6. **Effect of attention on choice.** The probability of choosing the left option as a function of the looking time advantage for the left alternative.

Figure 7. **No effect of value on fixation duration.** The duration of middle (i.e. neither first nor last) fixations does not depend on the subjective valuation of the fixated item. Thus, attention and value contribute independently to choice.

Figure 8. **Final fixation and choice.** The probability of choosing the left alternative not only depends on the value difference between the options, but also on the fixation pattern.
### Table 1. Effect of value on middle fixation duration.

Effects of subjective value of the fixated stimulus ($V_{fix}$) on the middle fixation duration of participants, with clustered standard errors. Only the risk task shows a significant relationship between valuation of the stimulus and fixation duration.

<table>
<thead>
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<th>Two-Food</th>
<th>Four-Food</th>
<th>Risk</th>
<th>Social</th>
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<tr>
<td>(Intercept)</td>
<td>0.681***</td>
<td>0.399***</td>
<td>0.340***</td>
<td>0.326***</td>
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<td></td>
<td>(0.045)</td>
<td>(0.016)</td>
<td>(0.011)</td>
<td>(0.009)</td>
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<td>$V_{fix}$</td>
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<td>0.002</td>
<td>0.001**</td>
<td>0.0002</td>
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<td></td>
<td>(0.007)</td>
<td>(0.002)</td>
<td>(0.0001)</td>
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`p < 0.1  *p < 0.05  **p < 0.01  ***p < 0.001`

### Table 2. Time advantage coefficient correlations.

Correlations are calculated within subjects across tasks in the attentional effect on their choices.

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<td>Four</td>
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<tr>
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<tr>
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<td>0.37’</td>
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<td>0.44*</td>
<td>0.52*</td>
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`p < 0.1  *p < 0.05  **p < 0.01  ***p < 0.001`


References


