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Attention and Choice Across Domains

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When people are faced with a decision, they tend to choose the option that draws their attention. In recent years, correlations between attention and choice have been documented in a variety of domains. This leads to the question of whether there is a general, stable relationship between attention and choice. Here, we examined choice behavior in tasks with and without risk and social considerations, using food or monetary rewards, within a single experiment. This allowed us to test the consistency of the decision-making process across domains. In the aggregate, we identified remarkable consistency in the attention-choice link. At the individual level, subjects with strong attentional effects in one task were likely to have strong attentional effects in the others. The strength of these effects also correlated with individuals' degree of tunnel vision. Thus, the attention–choice relationship appears to be a stable individual trait that is linked to more general attentional constraints.

Keywords: decision making, computational modeling, eye tracking, attention, individual differences

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In our daily lives, we make many different kinds of decisions, including what to eat for lunch, how to invest our money, and which charities to donate to. Traditionally, these different types of decisions have been studied in isolation, with only the overarching normative standard of utility maximization as a common thread. However, recent advances in decision neuroscience (Bartra, McGuire, & Kable, 2013; Clithero & Rangel, 2014) have indicated that there may be common mechanisms underlying these different decisions.

In particular, there has been much interest recently in the relationship between attention and choice (Arieli, Ben-Ami, & Rubinstein, 2011; Armel, Beaumel, & Rangel, 2008; Fiedler & Glöckner, 2012; Folke, Jacobsen, Fleming, & Martino, 2016; Johnson, Camerer, Sen, & Rymon, 2002; Krajbich & Rangel, 2011; Lohse & Johnson, 1996; Mormann, Navalpakkam, Koch, & Rangel, 2012; Orquin & Mueller Loose, 2013; Pärnamets et al., 2015; Polonio, Di Guida, & Coricelli, 2014; Shimojo, Simion, Shimojo, & Scheier, 2003; Stewart, Hermens, & Matthews, 2015; Venkatraman, Payne, & Huettel, 2014). Some of this work has used sequential sampling models (SSM) to model the links between gaze, response times (RTs) and choice probability (Ashby, Jekel, Dickert, & Glöckner, 2016; Cavanagh, Wiecki, Kochar, & Frank, 2014; Fisher 2017; Hutcherson, Bushong, & Rangel, 2015; Krajbich, Armel, & Rangel, 2010; Pärnamets, Richardson, & Balkenius, 2014; Towal, Mormann, & Koch, 2013), building off of earlier work that treated attention as a latent variable in the SSM process (Diederich, 2003; Roe, Busemeyer, & Townsend, 2001).

This past research into the effects of attention on decision making has explored choices in a variety of domains, including consumer goods (Folke et al., 2016; Mormann et al., 2012; Krajbich, Lu, Camerer, & Rangel, 2012; Towal et al., 2013), risky gambles (Fiedler & Glöckner, 2012; Lohse & Johnson, 1996; Stewart, Hermens et al., 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 (Ashby & Rakow, 2015; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Fiedler et al., 2013; Krajbich et al., 2010, 2012; Krajbich & Rangel, 2011; Stewart, Gächter, Noguchi, & Mullett, 2015; Stewart, Hermens et al., 2015). The influence of attention on choice occurs not only in decisions where subjects are allowed to freely look around but also in decisions where attention is exogenously manipulated (Armel et al., 2008; Lim, O'Doherty, & Rangel, 2011; Pärnamets et al., 2015).

What remains unclear is whether the relationship between attention and choice is the same across these different types of choices. If people employ a similar choice process across domains, one would expect quantitatively similar effects of gaze on choice,

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regardless of the decision at hand. Moreover, one might expect that a given individual displays stable effects, but that the effects across subjects are heterogeneous. Here, we sought to address these questions.

To do so, we developed an experiment where each subject completes several choice tasks while we track their eye movements. With this design, we are able to investigate both group- and individual-level behavioral consistencies across domains. This kind of comparison has been out of reach because prior studies have each explored only one domain in isolation. Thus, even though the influence of attention on choice has been demonstrated in many contexts, the interdomain consistency of the process has remained elusive.

To facilitate these comparisons, we utilize structural utility models from economics, in combination with regression analyses and a sequential sampling model. Sequential sampling models (SSMs) treat the decision-making process as a course of evidence accumulation. There are a variety of SSMs that adequately account for choice and RT data (Bogacz, 2007; Busemeyer & Diederich, 2002; Ratcliff & Smith, 2004). In the current article, we focus on predictions of the attentional drift diffusion model (aDDM; Krajbich et al., 2010).

In the traditional drift diffusion model (DDM), as people consider the alternatives in the choice set, they noisily gather evidence about each of the alternatives (Ratcliff, 1978). Once enough evidence is gathered for one option (relative to the other), the decision maker chooses it. Because the evidence accumulation is relative, evidence in favor of one alternative is evidence against the other. In the aDDM, this process is modulated by attention. Specifically, the decision maker accumulates more evidence for an item when they are looking at it than when they are not. This feature of the model predicts various relationships between gaze allocation and choice outcomes. Two relationships are of particular note and are the focus of our analyses.

The first relationship comprises dwell time and choice. The aDDM predicts that as subjects spend more time looking at an option (relative to the other), they will be more likely to choose that option. This is a straightforward prediction of the model because more dwell time produces more evidence for that option.

The second relationship is between the last-seen item and choice. The aDDM also predicts that subjects will tend to choose the option that they are currently looking at, unless that option is sufficiently worse than the other. This pattern arises because subjects accumulate more evidence for an option when they are looking at it than when they are not. Therefore, for a given pair of options A and B, it is more likely that the subject will choose A when looking at A than when looking at B (unless A is aversive). Even when A is sufficiently worse than B and the probability of choosing A is low, regardless of which option is currently looked at, the probability of choosing A is still higher when looking at A than when looking at B.

Here, we test these two critical aDDM predictions in our four choice tasks. In each domain, we identify model-consistent group-level effects of gaze on choice across all of the tasks. We also find consistent individual-level effects of gaze dwell time and final dwell location on choice, with significant between-task correlations. Finally, we see that these dwell-time (and to a lesser extent final-dwell) effects are correlated with a measure of “tunnel vision” that does not involve choices or eye-movements (Robertson, Kravitz, Freyberg, Baron-Cohen, & Baker, 2013).

Method

Subjects

In line with sample sizes in past research (Krajbich et al., 2010), 44 university students participated in this six-part study. Of these, 34 completed the entire experiment. Eight out of the 10 incomplete subjects completed alternative tasks in place of the social and money-risk tasks described below, and the other two experienced computer crashes in the psychophysical task. Thus, there are 44 complete food choice data sets (and among these, 36 complete value-based choice data sets). The Ohio State University Internal Review Board approved the experiment and subjects provided informed consent prior to participation.

Materials

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 eye-tracking data. Attentional areas of interest (AOIs) were defined a priori, each containing one of the stimuli on the screen. Subjects indicated all of their responses with button presses using a standard keyboard.

Task

In the first task, subjects rated their desire to eat each of 147 snack food items (chocolate, candy, chips, etc.) on a discrete scale from -10 to 10 (Figure 1a). Subjects were told that a rating of -10 should be used to 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. Subjects used the keyboard left/right arrow keys to move an on-screen indicator along the spectrum to the appropriate rating. Subjects were allowed as much time as they desired to complete this task. For more detail on the distribution of ratings, see the online supplemental material (Figure S16).

Subjects were then calibrated to the eye tracker and their eye movements were tracked for the remainder of the study. Subjects' left-eye fixation patterns and pupil diameter were recorded at 1000 Hz using an EyeLink 1000 Plus (SR Research, Osgoode, ON, Canada) eye-tracker, located 40.5 cm in front of the subject. The first eight subjects were run in “remote mode,” while the rest were run using the chinrest for improved data quality. All stimuli were presented on an LCD monitor (24′ XL2420TE, BenQ), located 79 cm in front of the subject. After the food rating task, subjects were calibrated using the standard nine-dot calibration procedure provided by the eye tracker's manufacturer.

Next, each subject completed four core choice tasks: two-food (Figure 1b), food-risk (Figure 1c), money-risk (Figure 1d), and social (Figure 1e) in a blocked design, by task. Each core task comprised 200 trials and these binary choice tasks were presented in a random order across subjects. In all four core choice tasks, subjects selected the left option by pressing the “F” key and the right option by pressing the “J” key on the keyboard. Additionally,

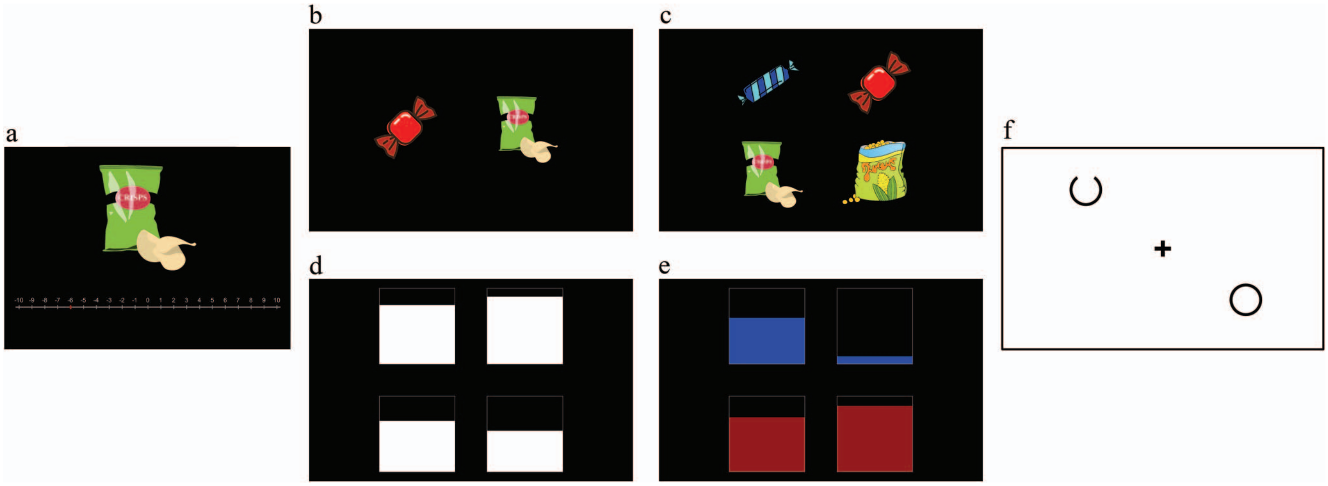

Figure 1. Experiment overview. (a) Subjects rated their desire to eat food items on a scale from −10 to 10. (b) Two-food: Subjects chose between two food items. (c) Food-risk: Subjects chose one of two 50–50 gambles over two foods (i.e., the left two foods or right two foods). (d) Money-risk: Subjects selected one of two 50–50 monetary gambles. The height of the white bar corresponds to the amount of money the subject would receive from that outcome. (e) Social: Subjects chose between two divisions of money between themselves and the next subject in the experiment. The height of the red (bottom) bar represents the subject's own payoff, while the height of the blue (top) bar represents the other subject's payoff. (f) Tunnel-vision task: Subjects fixated at the center of the screen, were cued to one side of the display, and then had to indicate whether the target, presented at different eccentricities from the midline, was pointed up or down. In the food tasks displayed above, the cartoon images are for illustration purposes only; in the experiment, subjects saw branded food items. See the online article for the color version of this figure.

there was no time pressure in any of the choice tasks; subjects took as much time as they wished to respond to each decision. In between trials, subjects were presented with a fixation cross in the center of the screen. Subjects automatically progressed to the next trial only after they had fixated on the cross for 1 s.

In the two-food task (Figure 1b), subjects 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. Only positively rated (i.e., rating >0) food items were included in this task, to ensure that subjects were choosing between items that were relevant to them. These positively rated items were randomly selected, subject to the constraints that (a) no item could be shown more than seven times and (b) the value difference between the items could not exceed five.

In the food-risk task (Figure 1c), subjects 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 subject chose the left option, he was selecting a lottery between the top left and bottom left food items. Again, only positively rated (i.e., rating >0) food items were included in this task. Similar to the two-food task, these items were randomly selected, subject to the constraints that (a) no item could be shown more than seven times and (b) the expected value difference (i.e., |average value left − average value right|) could not exceed four.

For each subject, 10,000 potential trials for the two-food and food-risk tasked were generated. Positively rated (i.e., rating >0) foods were randomly sampled as pairs (or quads, in the food-risk task), without any initial constraints on values or value differences. From these potential trials, any trials that did not fit the aforementioned constraints on value difference and item repetition were discarded. Many subjects (two-food: $n = 22$; food-risk: $n = 39$) did not have enough positively rated food items to generate 200 valid trials in each of the food choice tasks, so these subjects completed as many constraint-satisfying trials as were generated (two-food: $M = 171.3$; food-risk: $M = 146.7$). In the food tasks, we limited the difference in value between the options in order to increase the experiment's efficiency by focusing on trials with nontrivial decisions. This also facilitates the model fitting procedure, which relies on the RT distributions of "correct" and "error" choices.

The money-risk task (Figure 1d) was similar to the food-risk task in that each option consisted of an even-probability (i.e., 50/50) gamble. However, instead of food items, the outcomes 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 (the values of each box ranged from 0-300 pixels and were converted to dollars at the end of the study; subjects were informed of this structure). In each trial, 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 equate the stimuli in each task as much as possible, in order to focus on the psychological content of the outcomes. All subjects saw the same set of 200 gambles in a randomly presented order. Additionally, we randomized the location of the gambles (left vs. right) and the location of the two outcomes within each gamble (top vs. bottom) on each trial. The specific amounts used in the money-risk trials are included in the online supplemental material.

The social task (Figure 1e) used the same square stimuli as the money-risk task to represent amounts of money; this time, a fully filled square represented $5 (again, values ranged from 0-300 pixels and were converted to dollars at the end of the study; subjects were informed of this structure). However, in this task, each alternative consisted of a payoff for the subject (self: a red rectangle) and a payoff for the next subject (other: a blue rectangle). Here, subjects faced a tradeoff in each trial between selfishness and prosociality. The selfish option had the higher payoff (compared with the prosocial option) for the decision maker, whereas the prosocial option had a higher payoff (compared with the selfish option) for the next subject. We also varied the ordering of payoffs; that is, on some trials the current subject always earned more than the other, while on others, the current subject always earned less than the other. On a third type of trial, the earnings order (self vs. other) differed between the selfish and prosocial options. The specific amounts used in this task can also be found in the online supplemental material. We held colors (red/blue) constant across subjects, but counterbalanced the rows in which the payoffs (self/other) appeared across subjects such that self-payoffs were always in the same row for a given subject. We randomized the sides (left/right) on which the outcomes were displayed on each trial.

We incentivized every choice task; we randomly selected one trial from each of the domains (food, money-risk, and social) for compensation at the end of the study. For the social task, we delivered the "other" payoff to the next subject in the study. We did not inform subjects of the amount sent to them by the previous subject until after they had completed the entire experiment.

The last task in the experiment (Figure 1f) was a nonchoice task measuring attentional gradient, that is, the sharpness of an individual's scope of attention (Robertson et al., 2013). Central fixation was enforced throughout the task. On each trial, a small cue circle appeared for 67 ms at a visual angle of 7.89 degrees to one side of central fixation on the horizontal axis. This cue was always valid; it unequivocally indicated the side (left or right) of the forthcoming target. After a brief interstimulus interval (ISI; 67 ms, 135 ms, or 210 ms), a target and distractor appeared simultaneously and very briefly (67 ms), 180 degrees apart. The target appeared above or below the horizontal axis by one of three visual angles: near (2.44 degrees), middle (4.51 degrees), or far (6.57 degrees). The distractor (used to increase the effect of the cue) was a hollow circle, while the target was an incomplete hollow circle. The gap in the target was always at the top or the bottom of the circle; on each trial, the subject indicated the location of this gap using the up and down arrow keys, respectively. Subjects completed an initial staircase thresholding procedure on the background contrast to equate difficulty across subjects (see Robertson et al., 2013 for details); they then completed 11 trials at each combination of quadrant (above/below and left/right), distance (near, middle, and far), and ISI (short, medium, and long).

Following Robertson et al. (2013), trials with very long (more than two standard deviations above the log-transformed mean) or very short (<300 ms) RTs were removed from analysis (unlike Robertson et al., 2013, we used log-transformed RTs in our exclusion criteria because our RTs were log-normally distributed). Additionally, subjects were removed from analysis if they failed to perform at or above 75% accuracy at each distance from the horizontal median. Each subject's performance at each of the three distances was transformed into an efficiency measure:

$$-1 \times \left(\frac{medianRT}{proportioncorrect}\right).$$

Here, higher values indicate better performance. Thus, each subject had three efficiency scores, and an individual's calculated sharpness gradient is the difference in efficiency between the near and far locations. A larger sharpness gradient (greater fall-off in performance as the distance from the horizontal axis increases) indicates a narrower attentional scope.

Computational Modeling

Individual utility functions. An exponential utility function ($U(x) = x^{\rho}$) was fit to each subject for the money-risk task. On each trial, the likelihood of choosing the left option (with upper left and lower left potential outcomes V_{UL} and V_{LL}, respectively) is assumed to be

$$\left[1 + \exp\left(-\lambda \cdot \left(\frac{V_{UL}^{\rho} + V_{LL}^{\rho}}{2} - \frac{V_{UR}^{\rho} + V_{LR}^{\rho}}{2}\right)\right)\right]^{-1}$$

where ρ and λ are fitted subject-level parameters that best fit the observed data according to maximum likelihood (using a grid search with ranges $\rho = [-0.5,2]$ and $\lambda = [0, 5000]$). The corresponding estimates of ρ were used to transform the objective values in each gamble into subjective utilities (Figure S2a).

Similarly, we used the Charness-Rabin model (Charness & Rabin, 2002; Fehr & Schmidt, 2001) to account for individual differences in the social task:

$$U(x_i,\ x_j) = (1 - \beta r - \alpha s)x_i + (\beta r + \alpha s)x_j$$

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 $x_i < x_j$. Each subject's best-fitting α (disadvantageous inequality) and β (advantageous inequality) parameters were selected according to maximum likelihood (using a grid search with ranges $\alpha = [0, 0.5]$ and $\beta = [0, 0.75]$). Histograms of these subject-level parameters can be found in Figures S2b–2c in the online supplemental material.

The attentional drift diffusion model (aDDM). There are a number of parameters specified by the traditional DDM. This model was originally developed in the context of memory retrieval and has been used extensively in the modeling of perceptual decision making (Philiastides, Ratcliff, & Sajda, 2006; Ratcliff, 1978, 2002). In perceptual tasks, there is (almost) always an objectively correct answer, so the traditional implementation of the DDM frames each decision as correct versus incorrect. In this formulation, the drift rate (v) refers to the average rate of evidence accumulation, that is, the strength of the evidence for the correct response. As the choice gets easier (i.e., one alternative has increasingly more evidence relative to the other), the drift rate increases, leading to faster evidence accumulation and shorter RTs.

In noiseless choices, positive and negative drift rates would always lead to correct and incorrect answers, respectively. However, the choice process is inherently noisy, so erroneous/unexpected responses do occur, on occasion. The amount of noise (σ) is a parameter estimated in the model; noisier processes lead to more errors. The amount of relative evidence required to make a (correct) decision is known as the barrier separation (a). The starting point (z) is the initial position of the relative decision value (RDV), which is typically set to one half of the barrier separation ($z = a/2$). In our formulation, barriers are fixed at ± 1 (i.e., $a = 2$) and the process starts at a value of 0. In addition to the RT from the decision process, there is also a period of nondecision time (t_{er}) to account for processes such as orienting to the stimuli and the motor response.

At each time step, these parameters dictate the nature of added evidence, so the equation for evidence accumulation in the DDM is the following:

$$V_t = V_{t-1} + \nu + \varepsilon$$

where ν denotes the drift rate (the difference in subjective value between the two options) and ε is a random white-noise increment with mean zero and standard deviation σ. Technically speaking, this is a random walk model because it evolves in discrete steps rather than continuous time.

Traditionally, the only data available to sequential sampling modelers comes in the form of RTs and choices. However, in our value-based choice study, we have an additional dimension: gaze. Our subjects' eye movements are tracked during their decisions, so we thus reconceptualize the evidence accumulation process using a recent extension of the DDM: the attentional drift diffusion model (aDDM, Krajbich et al., 2010). The aDDM has an attentional discounting parameter, θ, which captures the effects of gaze on evidence accumulation—and thus, on choice. A crucial feature of the aDDM is that looking at one alternative results in a discounting of the unlooked-at option's value and thus a reduction in the rate of evidence accumulated for that alternative (Figure 2a). So, the drift rates in the aDDM are:

Gaze left: $\nu = d(U_L - \theta U_R)$
Gaze right: $\nu = d(\theta U_L - U_R)$

In both formulations, d is the drift scaling parameter used to convert the difference in subjective values (utilities, U_i) to a drift rate. When the two options are relatively close in value and θ is substantially lower than 1, shifts in gaze cause a reversal in the sign of the drift rate (Figure 2a). However, for two alternatives with a greater difference in value, the sign of the drift rate may not reverse, but instead only shrink toward zero (Figure 2b). We fit the aDDM in all four of our choice tasks at the group level (see online supplemental material for details). To get the most precise parameter estimates possible, we chose to fit the model to all of the data, rather than fit to only some of the data (e.g., for cross-validation).

To see how well the selected model parameters fit the data, we simulated a dataset for each task. In this simulated dataset, we inputted the gaze patterns (order and duration) observed in the subjects' actual data. If a simulated trial did not finish by the end of the gaze pattern observed in the data, then we sampled from all observed middle dwell times in the data until the trial terminated. As in Krajbich, Armel, and Rangel (2010), we count dwells ("fixations" in that article) as any time spent looking at a predefined AOI without looking at another AOI. Therefore, if the eye tracker registers a subject looking at one AOI, followed by a break from any of the AOIs (e.g., due to a blink), followed by looking again at the same AOI, then this would all be considered one dwell.

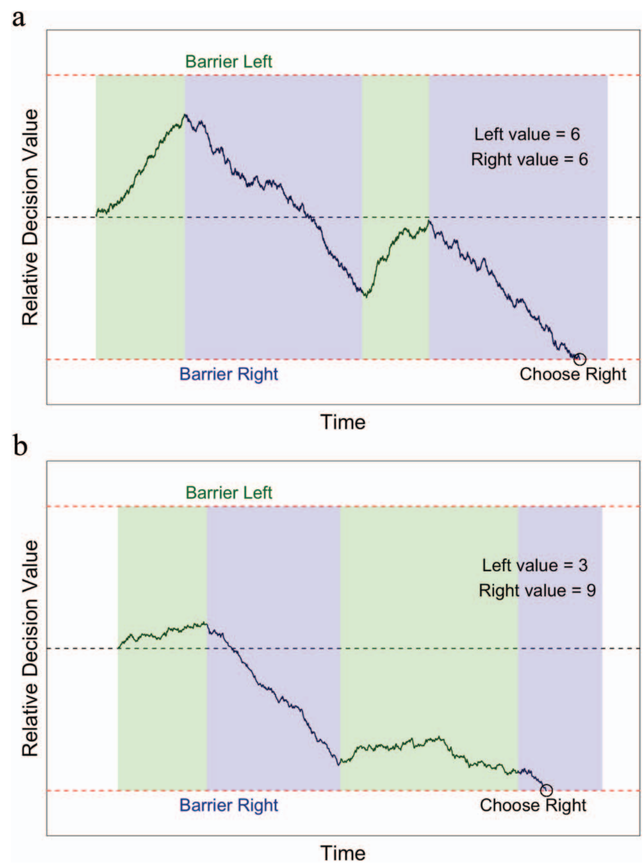

Figure 2. The attentional drift diffusion model (aDDM). The relative decision value begins at 0 and evolves over time until it reaches one of two predefined barriers at ± 1. The drift rate changes when gaze—denoted by the green (light gray) and blue (medium gray) regions—shifts between the left and right options, respectively. (a) A trial where the two options are equal in value, so the drift rates are equal and opposite. (b) A trial where the right option is much better than the left option, so the drift rate always favors the right option, just less so when gaze is on the left option. See the online article for the color version of this figure.

For an alternative version of the simulations, with random sampling of dwell times from the empirical distribution (as in Krajbich et al., 2010), see the online supplemental material (Figures S5–S8).

Group aDDM fitting. The aDDM was fit in each of the four tasks using maximum likelihood estimation (MLE). We did not fit the aDDM to the selfish subjects on the social task, because their behavior and eye movements suggest a visual search procedure, rather than a value-based comparison process that could be described by the aDDM. In the food-risk, money-risk, and social tasks, we recognize that there are multiple outcomes per alternative, but for comparison with previous binary choice paradigms (including the current two-food task), we treated each option (left/right) as one subjective value (the expected value of each gamble in the food-risk task, the expected utility in the money-risk task, and the fitted utility measure in the social task).

The general concept for fitting the aDDM is to find the parameters that generate simulated data most similar to the observed behavior from each task. To measure similarity between simulated and actual data, we binned both in the same manner and computed the likelihood of observing the data given the parameters.

How exactly to bin the data is a critical issue and not one with an obvious solution. In a "standard" DDM study there would be a small number of experimental conditions. Within each condition we would separate the data into correct and incorrect responses, and then further bin each set into RT quintiles. This method encountered some issues with our current study.

First, we did not have conditions; every trial was a unique choice problem with different tradeoffs. Therefore, we had to try to normalize utilities across subjects and then bin those normalized utilities. We could not use z-scored utilities because greater attention to negative values (i.e., any z-scored utilities below the mean) yields a decrease in the evidence for that alternative (see Armel et al., 2008). None of our stimuli were aversive, so using negative values in the aDDM would be inappropriate. Therefore, expected utilities in the money-risk and social tasks were linearly transformed at the individual level to a 0–10 interval in order to match the subjective value scale in the food-choice tasks. The rescaled expected utilities were then divided into five utility difference bins such that there were an equal number of trials in each bin. Subjective expected values in the food-risk task were rounded to the nearest whole number (1–10). This yielded five value difference bins in the food-risk task (0, 1, . . . 4). We did not bin the two-food task, so there were six value differences (0, 1, . . . 5).

Second, standard DDM fitting methods place a strong emphasis on RT distributions in order to identify drift-rate, barrier-separation, starting-point, and noise parameters. However, RT distributions are not well suited to identify the attention parameter θ. We thus attempted to incorporate eye-tracking measures into our fitting procedure. After splitting the data into correct and incorrect subsets at each absolute value difference (except zero), we further split the data into terciles based on dwell time advantage for the correct alternative (i.e., total dwell time on correct minus total dwell time on incorrect). Finally, within each of these dwell-time terciles, we split the data into fast and slow halves, using that tercile's median RT. For trials with a value difference of zero, we simply pooled all the trials before separating the data based on dwell-time terciles (total dwell time left minus total dwell time right) and median RT (see Figure S3 for an illustration of this binning process).

For each set of potential parameters, our fit procedure generated a simulated dataset that contained 10 simulations per trial in each subject's data. To simulate each trial, we used the exact sequence of gaze locations and dwell times from the data. Whenever a simulation did not reach a barrier by the time the subject had actually decided, we continued the simulation using alternating gaze locations (e.g., left, right, left, . . .) and randomly selected dwell times, which we sampled from the pool of all observed middle (i.e., neither first nor last) gazes. With this simulated dataset in hand, we then separated the simulated trials by subjective value difference, correct/incorrect choices, dwell-time advantage (according to the data terciles), and RT (according to the data median split), and then calculated the log-likelihood of the data given the model.

To establish the proper parameter range over which to search for each task, we tested 10,000 parameter combinations for each task. The initial ranges for the parameters were as follows: $d = [0, 0.001$ per ms$]$, $\sigma = [0, 0.05]$, $\theta = [0, 1]$, $t_{er} = [0, 1000$ ms$]$. Parameter combinations were randomly generated from a wide range in order to maximize the utility of the search (Bergstra & Bengio, 2012).

Each set of parameters yielded a likelihood statistic; the parameter sets were rank-ordered from best to worst according to this fit metric. In the top 1% of parameter combinations, the ranges for d, σ, and t_{er} were identified and used as the ranges for a second iteration. A similar strategy was used for the third iteration; the top 0.5% parameters from the first and second iteration were used to generate the ranges for the parameters. Because θ is the main parameter of interest in this study, we kept the bounds on θ at [0, 1] for all three iterations.

After three iterations, we identified the best fitting parameter set according to the likelihood metric. The final set of parameters for each task, then, is the set of parameters that maximizes the similarity between the simulated data and the actual data.

Results

Behavioral Findings

To account for differences in risk aversion and prosocial tendencies in later analyses, the values in the money-risk and social choice tasks were reframed using individual-level utility functions: a standard exponential utility function for money-risk and an inequity-aversion model for social (Charness & Rabin, 2002; Fehr & Schmidt, 2001; see online supplemental Method section). Because of the arbitrariness of utility magnitude and the variability that exists across individuals, utility values were z-scored within each subject for each task in order to yield a more standardized measure of subjective value (except in the aDDM fitting). The money-risk and social task results will henceforth be discussed in terms of this standardized utility measure, while the two-food and food-risk choice findings will continually be interpreted according to the utilities from the initial rating task.

Before proceeding, we must first address a unique feature of the social choice task. In particular, subjects differed considerably on the ratio of selfish/prosocial options that they selected (Figure S1). The distribution of selfish choice proportions was relatively bimodal, with a sizable group of subjects ($n = 14$) choosing the selfish option nearly every time (>90%). This purely selfish behavior (allowing for some perceptual noise) is well-documented in the social choice literature (Camerer, 2003; Liebrand & McClintock, 1988) but poses a potential problem for our analyses because these subjects might not be making "decisions" in the traditional sense and instead simply looking for the bigger red box on each trial. That is, some subjects (i.e., the purely selfish ones) are able to completely ignore one of the attributes in each choice (i.e., the other subject's payoffs) while still making preference-consistent choices because the other subject's payoffs are irrelevant in this case. This is a unique feature of the social task; in the other tasks, both attributes are relevant, regardless of subjects' preferences. Therefore, for several analyses we split the subjects into two separate groups (pure selfish, $n = 14$ vs. prosocial, $n = 22$) and report their results separately on the social task. The behavioral difference between prosocial and selfish subjects extends to the eye-tracking data as well (see the online supplemental material).

Group-Level Behavioral Comparisons

In the two-food and food-risk tasks, subjects' choices were highly consistent with their prior ratings (two-food: mixed-effects logistic regression of *choose left on rating difference* (left—right) ($\beta = 0.44$, $p < 10^{-16}$, with nonsignificant *intercept* $= 0.02$, $p = .46$); food-risk: mixed-effects logistic regression of *choose left* on *mean rating difference* ($\beta = 0.53$, $p < 10^{-16}$, with nonsignificant *intercept* $= 0.01$, $p = .88$).

In the other two tasks, there is no objective measure of correctness (which is why we need individual utility functions), but we do find a marginal effect of subjects choosing in line with expected value in the money-risk task (mixed-effects logistic regression of *choose left* on *mean value difference*, $\beta = 0.02$, $p = .15$, with nonsignificant *intercept* $= 0.06$, $p = .26$). The selfish subjects' choices fall in line with their own values in the social task, while the prosocial subjects' choices are correlated with both their own payoffs and the other's payoffs (mixed-effects logistic regression of *choose left* on *own value difference*, selfish: $\beta = 0.21$, $p = 10^{-8}$; prosocial: $\beta = 0.03$, $p = 10^{-7}$; and *other value difference,* selfish: $\beta = 0.002$, $p = .31$; prosocial: $\beta = 0.01$, $p = .001$; with nonsignificant *intercept*, selfish: 0.07, $p = .70$; prosocial: 0.01, $p = .90$).

By definition, subjects' choices were in line with their utility differences, as predicted by the model (Figure 3a–d). While the selfish subjects exhibited a step-like choice curve on the social task, the other four curves resembled a standard logit and had a high degree of overlap (Figure 3e).

That being said, this consistency falls out of predictions made by the aDDM and can be seen in the model-fitted simulations: As the left option gets increasingly better than the right option, the drift rate becomes increasingly positive. A drift rate further from zero (where zero indicates complete indifference) translates to more rapid accumulation of evidence to a boundary. As a result, the decision maker chooses the (better) left option with a higher probability and more quickly.

A core feature of SSMs is that the hardest decisions take the longest to make; that is, RT increases as the absolute drift rate decreases. This result has been replicated in a variety of value-based decision domains (Busemeyer, 1982, 1985; Busemeyer & Townsend, 1993; Cavanagh et al., 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, 2014; Krajbich & Rangel, 2011; Mormann, Malmaud, Huth, Koch, & Rangel, 2010; Petrusic & Jamieson, 1978; Philiastides & Ratcliff, 2013; Polanía, Krajbich, Grueschow, & Ruff, 2014; Stewart, Gächter et al., 2015; Towal et al., 2013).

In our study, all four tasks indeed demonstrated an inverse relationship between absolute utility difference and RT (Figure 4a–d; mixed-effects regression of *log*(*RT*) on *absolute utility difference*, two-food: $\beta = -0.04$, $p = 10^{-9}$; food-risk: $\beta = -0.04$, $p = 10^{-9}$; money-risk: $\beta = -0.17$, $p = .003$; social, prosocial: $\beta = -0.41$, $p = 10^{-7}$; social, selfish: $\beta = -0.68$, $p = 10^{-6}$). The model-fitted simulations demonstrate a similar negative correlation between subjective value difference and RT.

Although this RT–difficulty pattern is consistent across the different tasks, the tasks do differ to some extent in the speed with which subjects take to complete them (Figure 4e). While the three

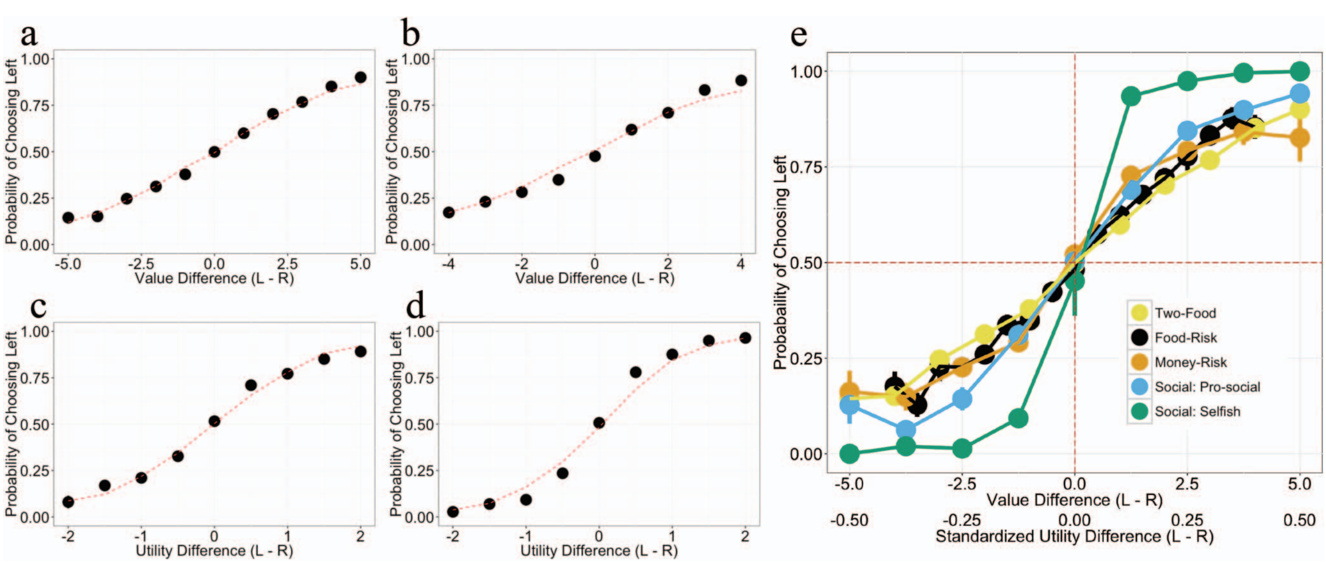

Figure 3. Effect of utility on choice. Probability of choosing the left option as a function of the utility difference between the two options, for (a) two-food choice, (b) food-risk choice, (c) money-risk choice, and (d) social choice. Black circles represent data while red (gray) dashed lines represent attentional drift diffusion model (aDDM) simulations. The simulations take subjects' actual gaze patterns from each trial as inputs; each trial is simulated 10 times (with noise only in the diffusion process) to create the simulated dataset. (e) All four choice curves overlaid, with z-scored utility for the money-risk and social tasks. The x-axes in (c) and (d) are not z-scored utility because the model uses the raw utilities (see Method). Bars represent *SEM* clustered by subject. See the online article for the color version of this figure.

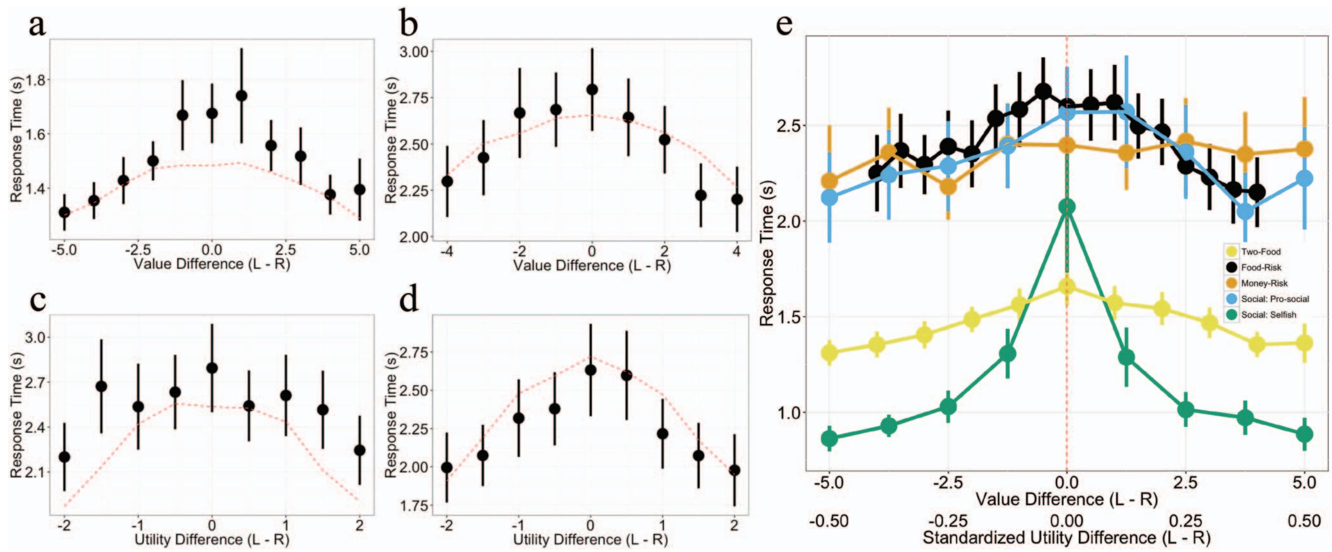

Figure 4. Effect of utility on RT. Mean RT as a function of the utility difference between the two options, for (a) two-food choice, (b) food-risk choice, (c) money-risk choice, and (d) social choice. Black circles represent data while red (gray) dashed lines represent attentional drift diffusion model (aDDM) simulations. The simulations take subjects' actual gaze patterns from each trial as inputs; each trial is simulated 10 times (with noise only in the diffusion process) to create the simulated dataset. (e) All four RT curves overlaid, with *z*-scored utility for the money-risk and social tasks. Bars represent *SEM* clustered by subject. See the online article for the color version of this figure.

tasks with four items were quite similar in terms of mean RT (food-risk: M = 2.68 s; money-risk: M = 2.66 s; prosocial: M = 2.32 s), subjects were considerably faster on the two-food task (M = 1.59 s) and the selfish subjects on the social task were faster still (M = 1.12 s). These results make sense; the more outcomes that need to be evaluated, the longer the decision should take. For selfish subjects, the choice was a simple perceptual size comparison, so they made their choices significantly faster, on average, than the prosocial subjects, $t(27.23) = -4.58$, $p = 10^{-5}$.

Group-Level Eye-Tracking Comparisons

The aDDM makes two key predictions regarding the relationship between eye-movements and choice behavior. The first is a positive relationship between choice probability and the difference in dwell time between the two options (Figure 5a–d). That is, the more overt attention an item receives, the more likely it is to be chosen. This relationship was remarkably consistent across the tasks in our experiment (Figure 5e; mixed-effects logistic regression of *choose left* on *dwell-time difference* (in seconds), two-food: $\beta = 1.68$, $p < 10^{-16}$; food-risk: $\beta = 1.48$, $p = 10^{-16}$; money-risk: $\beta = 2.00$, $p = 10^{-9}$; social, prosocial: $\beta = 1.30$, $p = 10^{-10}$; social, selfish: $\beta = 0.97$, $p < 10^{-16}$; *utility difference* was also included as an independent variable in each regression). 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) corresponded to a ~25% increase in the likelihood of choosing the left option, regardless of task.

At first glance, it seems as if the selfish subjects are more affected by their attention than the prosocial subjects, according to the strength of the attention–choice relationship observed in Figure 5e. However, as seen in the regression results, the selfish subjects display a smaller effect ($\beta = 0.97$) than their prosocial counterparts ($\beta = 1.30$). This discrepancy between high (in the graph) and low (in the model) attentional influence can be explained by the fact that selfish subjects' attention was drawn to the higher self-amounts. This leads to an increased rate of choice for the more-attended alternative, but the driving force of this effect lies in the values of the alternatives, rather than the attention paid to them. Therefore, after accounting for the payoffs, the effect of gaze on choice is largely diminished for the selfish subjects, especially in comparison to the prosocial group.

One factor in the consistency of this attention–choice link across all tasks is the absence of aversive stimuli in any of the choice sets. Research (Armel et al., 2008) has demonstrated that increased attention to negatively rated food items results in a decrease in the likelihood of choosing that alternative. However, even the outcomes that were worth less than 20% of the maximum valuation in each task (ratings of 1 or 2 in the food tasks and values less than \$1 or \$2 in the social and money-risk tasks, respectively) showed a positive relationship between dwell time and the likelihood of choosing that option (mixed-effects logistic regression of *choose left* as a function of *dwell time left* for the lowest 20% of outcomes: two-food: $\beta = 0.90$, $p = 10^{-10}$; food-risk: $\beta = 0.52$, $p = .001$; money-risk: $\beta = 0.56$, $p = .04$; social, prosocial: $\beta = 1.14$, $p = .003$; social, selfish: $\beta = 1.44$, $p = .50$). The only exception to this significant trend is the selfish subjects in the social task, which aligns with the idea that these subjects are not using an aDDM process.

The aDDM also predicts a relationship between the relative utilities of the options and the probability that the last seen option

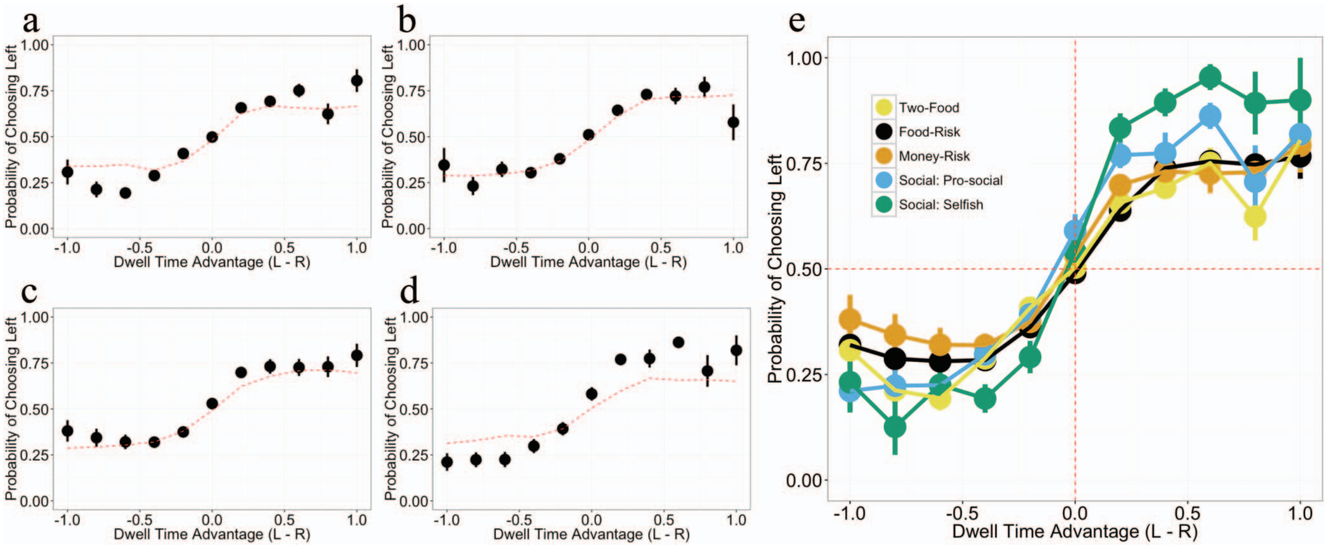

Figure 5. Effect of dwell time on choice. Probability of choosing the left option as a function of the trial-level dwell-time difference (in seconds) between the left and right options, for (a) two-food choice, (b) food-risk choice, (c) money-risk choice, and (d) social choice. Black circles represent data while red (gray) dashed lines represent aDDM simulations. The simulations take subjects' actual gaze patterns from each trial as inputs; each trial is simulated 10 times (with noise only in the diffusion process) to create the simulated dataset. (e) All four choice curves overlaid. Bars represent *SEM* clustered by subject. See the online article for the color version of this figure.

is chosen (see Figure 6). In particular, it predicts that the last seen option is usually the chosen option, but that this probability decreases when the last seen option is significantly worse than the other option. In other words, there are cases when a subject is looking left but suddenly chooses right—without looking right—and this tends to occur when the left option is substantially less valuable than the right option. If attention to an alternative yielded no advantage in evidence accumulation (i.e., $\theta = 1$), then the location of the last gaze would not affect choice proportions. In this case, the two choice curves would be indistinguishable and Figure 6 would be identical to Figure 3. However, the separation of the two curves indicates a clear attentional effect. Importantly, the separation of these two curves is remarkably consistent across the four tasks, with a ~70% chance of choosing the last seen item when subjects are indifferent between the two options (i.e., utility difference = 0). To illustrate this consistency, we estimated the following logistic choice model for each subject in each task:

$$P(ChooseLeft) = \beta_0 + \beta_1(U_L - U_R) + \beta_2(FinalDwellLeft) + \beta_3(|U_L - U_R|) + \beta_4((|U_L - U_R|) \cdot FinalDwellLeft)$$

Here, U_L and U_R are the left and right subjective values, respectively, and *FinalDwellLeft* is a binary variable indicating the location of the final dwell (1 for left, 0 for right). Therefore, the coefficient on *FinalDwellLeft* documents the size of the gap between the two choice curves at a value difference of zero. We computed a pairwise, paired *t* test on β_2 between the different tasks. None of the tasks were significantly different from each other, even without correcting for multiple comparisons (all non-corrected $ps > 0.1$). A one-way ANOVA also did not reveal significant differences between the tasks, $F(3, 80.40) = 1.22$, $p = .34$. We also estimated a logistic mixed effects model (using a Bayesian approach) for each task; the 95% confidence intervals for β_2 overlapped for all tasks, although the lower bound for the selfish subjects was substantially closer to zero than the lower bounds for the rest of the tasks, indicating a less substantial final dwell effect (two-food: [1.56, 2.26]; food-risk: [1.34, 2.15]; money-risk: [1.73, 2.57]; social, prosocial: [1.40, 2.36]; social, selfish: [0.06, 2.41]).

Intuitively, it seems that the effect of attention on choices might be explained simply as a tendency to look first or look more at high-value outcomes (i.e., highly rated food items and large monetary amounts in the money-risk/social tasks). However, consistent with prior results, the data suggest that there is little (if any) relationship between gaze and value (see Figure 7). Additionally (and importantly), subjects did not always look at their chosen item last. In fact, they only looked at their chosen item last in 70%, 68%, 75%, 74%, and 76% of trials in the two-food, food-risk, money-risk, and social (prosocial subjects and selfish subjects) tasks, respectively.

The duration of middle dwell times (any gaze that is neither the first nor the last in a trial) are generally unrelated to the value of the attended item/amount on the screen. Middle dwell times (as opposed to first or final dwell times) are used in this analysis to preserve homogeneity. First and final dwell times are significantly shorter than middle dwell times, on average, both in the current study (two-sample *t* tests, all $ps < 10^{-16}$) and in previous literature (Krajbich et al., 2010). Table 1 outlines the Bayesian mixed effects linear regression models for each task, in which middle dwell times are regressed on the gazed-at outcome's utility (traditional mixed-effects regressions did not converge for these analyses). We see that the value of the gazed-at item does not typically influence the middle dwell time (Figure 7e).

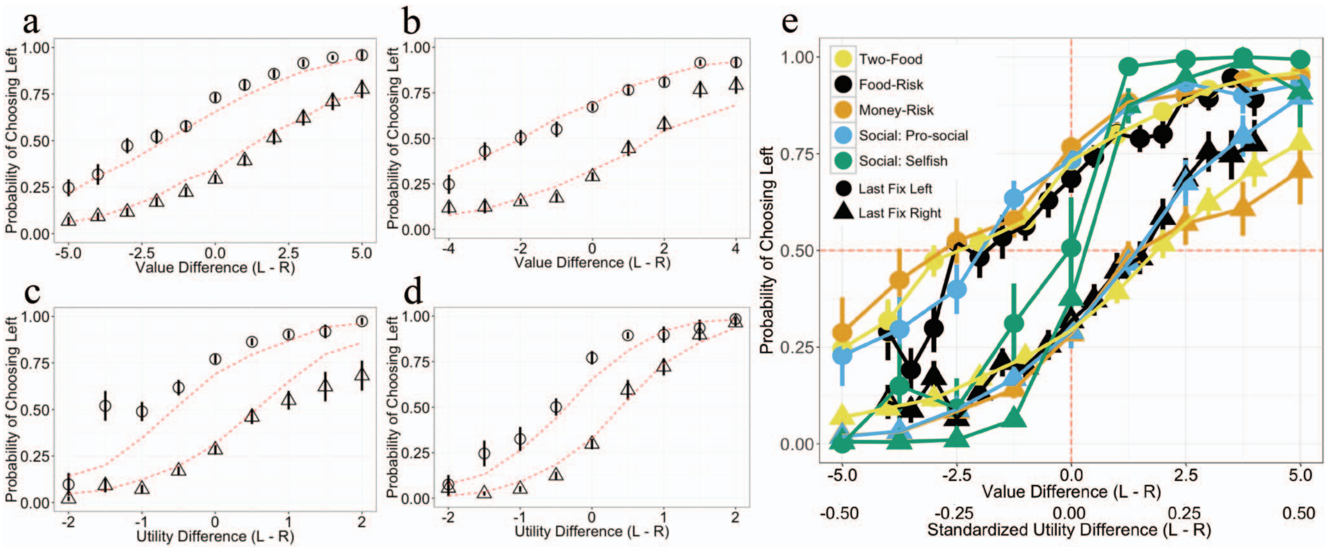

Figure 6. Effect of last gaze on choice. Probability of choosing the left option as a function of the utility difference between the two options, split by the location of the last gaze, for (a) two-food choice, (b) food-risk choice, (c) money-risk choice, and (d) social choice. Black circles represent data while red (gray) dashed lines represent aDDM simulations. The simulations take subjects' actual gaze patterns from each trial as inputs; each trial is simulated 10 times (with noise only in the diffusion process) to create the simulated dataset. (e) All four choice curves overlaid, with *z*-scored utility for the money-risk and social tasks. Bars represent *SEM* clustered by subject. See the online article for the color version of this figure.

Previous research (Krajbich et al., 2010) has demonstrated the absence of any significant relationship between the subjective value difference between two alternatives and the probability that the more valuable option is looked at first in a given trial. A similar pattern holds in this research (Figure 7a–c). The only discrepancy we see is for the selfish subjects in the social task (Figure 7d), who show a significant increase in the likelihood of looking at the selfish option first as the difference between self-payoffs gets larger (mixed effects logistic regression of *look at higher self-amount first* on *absolute difference in*

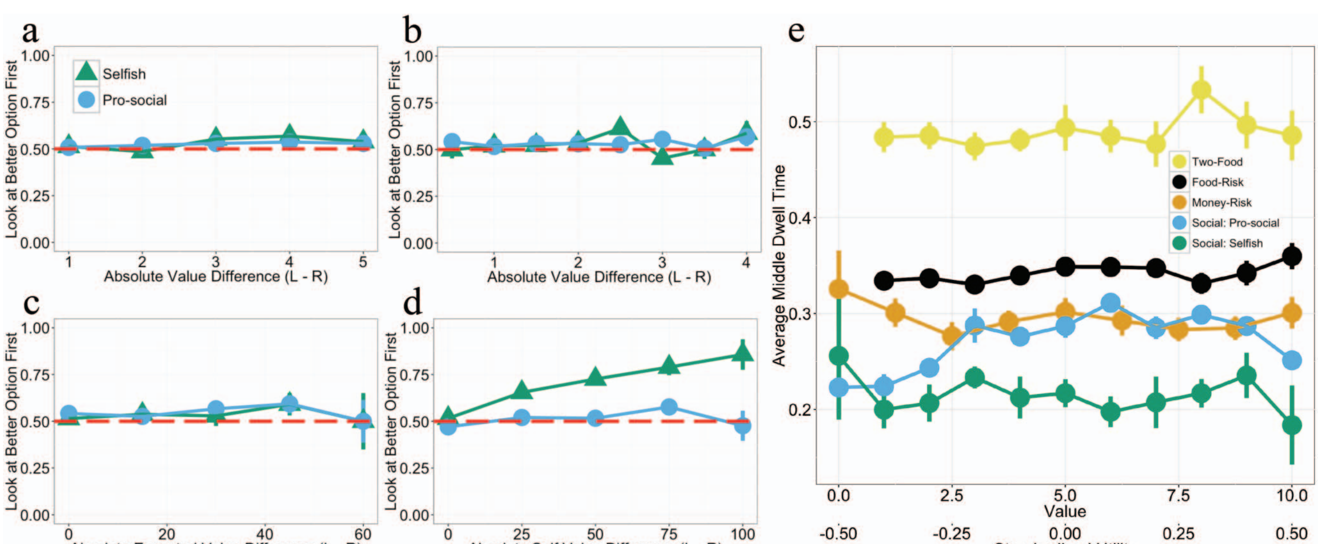

Figure 7. Relationship between utility and gaze. Probability of looking at the higher-utility option first, for (a) two-food choice, (b) food-risk choice, (c) money-risk choice, and (d) social choice. Blue (light gray) circles represent prosocial subjects while green (medium gray) triangles represent selfish subjects. (e) Mean dwell times (in seconds) as a function of the utility of the looked-at ROI, for all four tasks. Bars represent *SEM* clustered by subject. See the online article for the color version of this figure.

Table 1
Effect of Utility on Middle Dwell Duration

	Effect of value on middle dwell time				
Coefficient	Two-food	Food-risk	Money-risk	Social: Prosocial	Social: Selfish
(Intercept)	.65 (.045) [.56, .74]	.36 (.011) [.34, .39]	.28 (.015) [.25, .31]	.30 (.013) [.27, .33]	.36 (.12) [.13, .59]
Utility	.00030 (.0076) [−.014, .015]	.0019 (.0010) [−.00020, .0039]	.0077 (.0021) [.0035, .012]	.0016 (.0011) [−.00060, .0038]	−.0014 (.012) [−.024, .022]

Estimate (Standard Error) [95% CI]

Note. Effects of utility of the gazed-at stimulus on the middle dwell times of participants, estimated using Bayesian regression. Only the money-risk task shows a significant relationship between dwell time and stimulus value.

self amounts, $\beta = 0.02$, $p = .002$). This finding is perhaps the best indicator of two distinct strategies—largely separable by social tendency—that our subjects utilized. While the prosocial subjects seemingly engaged in a process of evidence accumulation as they looked from one option to the other, the selfish subjects only needed to find the higher amount and choose it. There is simply very little role attention can play in choice when the choice has already been made.

Group-Level aDDM Fits

The best fitting parameters for each task were: two-food: $d = 0.00023\ \mathrm{ms}^{-1}$, $\sigma = 0.029$, $\theta = 0.44$, $t_{er} = 425$ ms; food-risk: $d = 0.00013\ \mathrm{ms}^{-1}$, $\sigma = 0.017$, $\theta = 0.13$, $t_{er} = 103$ ms; money-risk: $d = 0.00031\ \mathrm{ms}^{-1}$, $\sigma = 0.019$, $\theta = 0.65$, $t_{er} = 209$ ms; social: $d = 0.00029\ \mathrm{ms}^{-1}$, $\sigma = 0.016$, $\theta = 0.69$, $t_{er} = 33$ ms. In each combination, d is the drift rate multiplier, σ is the standard deviation of white noise increments, θ is the discounting factor on the nonattended alternative, and t_{er} is the nondecision time.

It is worth noting that the utility differences in the social and risk task were scaled for the model so that nearly all trials fell in the range from −2 to +2 (97% of trials in the money-risk task, 96% in the social task), while in the food-risk task the range was −4 to +4. This helps to explain why d is half as large in the food-risk task compared with the two others. These drift rates are in turn only half as large as in the two-food task, presumably because only half of an option's outcomes are being considered during any given gaze. It is also worth noting that our nondecision times are unusually low, which is likely the result of our fitting method. We chose to sacrifice precision in RTs in order to better estimate the attention parameter θ.

Among the risk tasks (food-risk and money-risk), we acknowledge that there is a discrepancy in the fitted theta values (0.13 and 0.65, respectively), but in Figure 5e (and to some extent Figure 6e), we see that the attentional effects are quite similar. Looking at Figure 6b–c, we see that the model predictions in the food-risk task seem to slightly overestimate the effects of the final dwell (i.e., the red curves should be closer together), while the predictions for the money-risk task seem to underestimate the effects of the final dwell (i.e., the red curves should be further apart). The gaze effects seem to be slightly underestimated in social task as well (Figure 6d). We suspect that this may have something to do with the fact that these latter two tasks' fits depend on inferred utilities rather than explicit ratings because the model assumes a cardinal value scale. The multiattribute nature of these tasks also means that there is unaccounted-for variability in the model.

Individual-Level Analyses

Having established that there were consistent group-level relationships between utility, eye-movements, and choice, across the four tasks, we next sought to investigate whether this consistency held at the individual level. That is, were some subjects consistently more or less influenced by attention in their choices? To investigate this notion, we estimated the following logistic regression model for each subject, for each task:

$$P(ChooseLeft) = \beta_0 + \beta_1(U_L - U_R) + \beta_2(D_L - D_R)$$

In this model, U_L and U_R correspond to the values of the left and right options, respectively. In the food-risk and money-risk tasks,

U_L and U_R are the expected subjective values of each alternative, based on the food ratings supplied by the subjects and the utilities supplied by the fitted exponential utility model. In the social task, U_L and U_R are utilities from the Charness-Rabin model. Thus, $U_L - U_R$ is a value difference measure, used here as a covariate to account for the fact that subjects tend to choose in line with their utilities. The primary coefficient of interest is β_2, which is attached to the dwell-time advantage measure, given by $D_L - D_R$. Here, D_L and D_R refer to the total dwell time on a given trial for the left and right alternatives, respectively.

This logistic regression model gives us clear insight into the effects of attention on an individual's choices in one domain. In fact, simulations of the aDDM at varying levels of attentional influence (i.e., different values of θ) demonstrate a near-perfect correlation with the fitted logistic regression coefficients on dwell-time advantage and we find similar correlations between individually fitted θ values and logistic coefficients in the data (for more details, see the online supplemental material). To determine the consistency of individual-level attentional influence, we computed pairwise correlations between the tasks of the time advantage coefficients across subjects. Strong positive correlations, therefore, indicate that subjects who are highly affected by gaze in one task are also highly affected by gaze in another. The results of these correlations, across all subjects, appear in Table 2. Clearly, there are robust subject-level consistencies among the two-food, food-risk, and money-risk tasks. At first glance, though, the social task appears to be devoid of any meaningful correlation.

However, this insignificance is driven by the selfish subjects. When the data are split according to social preference, the selfish subjects still demonstrate no correlation between their dwell-time advantage coefficients in the social task and the coefficients in the other tasks. Among the prosocial subjects, though, the magnitude of attentional influence on choice is consistent across all domains, including the social task (see Table 2).

These dwell-time coefficient correlations represent our core finding: They demonstrate strong evidence for a consistent individual-level attentional effect on choices across multiple domains (at least for prosocial subjects). They provide evidence, therefore, for a domain-general choice process, moderated similarly (within a person) by attention to the alternatives. Looking at the effect of final-dwell location on choice also provides evidence for a common cross-domain attention mechanism (see Table 3).

Another difference between the social task and the other four-stimuli tasks (the food-risk and money-risk tasks) is that subjects tended to make more within-option dwell transitions (i.e., from the top row to the bottom row or from the bottom row to the top row within the same option) than between-option transitions (i.e., from one side of the screen to the other) in the food-risk and money-risk tasks. On the other hand, in the social task, subjects (and especially the selfish subjects) tended to make more between-option transitions than within-option transitions (see Figure 8). Despite this difference, we do not find that the transition proportions (average proportion of within-option transitions divided by average proportion of between-option transitions) among the prosocial subjects in the social task were related to the proportion of prosocial choices, $r(20) = 0.13$, $p = .56$. Similarly, in the money-risk task, the ratio of transitions (within-option divided by between-option) was not related to the number of risky choices, $r(34) = -0.02$, $p = .92$ or the number of expected value (EV) maximizing choices, $r(34) = -0.001$, $p = .97$. In the food-risk task, we also do not see a relationship between EV-maximizing behavior and transition proportions, $r(42) = -0.19$, $p = .21$. Moreover, we do not find any significant correlations between the subject-level transition proportions in a given task and the associated effect of attention on choice (logistic dwell-time coefficients, as in Table 2), all ps > 0.4. Therefore, we do not have any evidence to suggest that the magnitude of attentional influence depends on transition patterns, and this is a consistent null finding across all of the tasks. Ultimately, although subjects differ in their transition behavior within and across tasks, we do not see any associated difference in attentional influence on choice.

Table 2
Dwell Time Advantage Coefficient Correlations

Task	Two-food	Food-risk	Money-risk
	All participants (n = 36)		
Food-risk	$.62^{***}$		
Risk	$.71^{***}$	$.56^{***}$	
Social	$.41^{*}$	.20	.24
	Prosocial participants only (n = 22)		
Food-risk	$.65^{**}$		
Risk	$.64^{**}$	$.48^{*}$	
Social	$.46^{*}$	$.42^{*}$	.35
	Selfish participants only (n = 14)		
Food-risk	$.67^{***}$		
Money-risk	$.91^{***}$	$.78^{***}$	
Social	.26	−.10	.05

Note. Correlations are calculated within subjects across tasks. The correlation between the money-risk and social tasks in the prosocial subgroup has a p-value of .107.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Determinants of the "a" in aDDM

The results above suggest that the extent to which attention influences one's choices varies across individuals. This means that some individuals may be more susceptible to attention manipulations (e.g., marketing) than others. The question then is what factors might influence and/or predict the size of the effect? One idea is that an individual's attentional scope (i.e., their degree of "tunnel vision") might play an important role, particularly in visually guided decision making. It is already known that people differ in the breadth of their attentional scope (Robertson et al., 2013); while some have a very broad scope and therefore attend to a larger proportion of their visual field, others have a narrow scope and are less sensitive to stimuli far from the focus of their attention. In terms of the aDDM, we hypothesized that a broader scope of attention (smaller sharpness gradient) would enable a more even comparison of the alternatives, while a narrower scope (larger sharpness gradient) would instead correspond to a larger change in the drift rate as gaze shifts from one option to the other.

To test this idea, we used the results from the psychophysical task (Robertson et al., 2013; Figure 1f) to measure the breadth of their attentional scope. Following Robertson et al. (2013), we calculated subjects' performance on the task as the ratio of RT to accuracy, and the difference in this measure for close versus far

Table 3
Final Dwell Coefficient Correlations

Task	Two-food	Food-risk	Money-risk
All participants (n = 36)			
Food-risk	.34*		
Money-risk	.49**	.42*	
Social	.42**	.54***	.40*
Prosocial participants only (n = 22)			
Food-risk	.35		
Money-risk	.41†	.15	
Social	.34	.50*	.26
Selfish participants only (n = 14)			
Food-risk	.40		
Money-risk	.67**	.82***	
Social	.42	.63*	.42

Note. Correlations are calculated within subjects across tasks. The model includes the signed value difference between the options, as well as the location of the final dwell.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

targets was the measure of attentional scope (sharpness gradient). As we hypothesized, the psychophysical task did account for some individual variation in the choice tasks. A narrower scope (i.e., a greater decline in task performance for far vs. close targets) corresponded to a higher percentage of trials in which subjects chose the more attended option (based on total dwell time), Pearson's $r(30) = 0.37$, $p = .04$. In other words, subjects with narrower scopes were more likely to choose the more-looked-at alternative.

Some of the subjects ($n = 4$) exhibited a negative sharpness gradient (which indicates that their response efficiency improved as the target stimuli moved further from the horizon). However, the correlation between attentional scope and attentional influence on choices was still marginally significant if these subjects were excluded, Pearson's $r(26) = 0.31$, $p = .10$.

Breaking these results down into the individual tasks and measures (dwell-time and final-dwell effects on choice from Tables 2–3), we find significant correlations for three out of four of the dwell-time-effect correlations with sharpness gradient: two-food: $r(30) = 0.41$, $p = .02$; food-risk: $r(30) = -0.04$, $p = .85$; money-risk: $r(25) = 0.56$, $p = .0006$; social (combined): $r(25) = 0.40$, $p = .04$; social (prosocial): $r(17) = 0.43$, $p = .07$; social (selfish): $r(6) = 0.43$, $p = .30$, while we find only one (and a second marginal) significant correlation for the final-dwell-effect correlations with sharpness gradient: two-food: $r(30) = 0.03$, $p = .88$; food-risk: $r(30) = -0.32$, $p = .08$; money-risk: $r(25) = 0.30$, $p = .13$; social (combined): $r(25) = -0.49$, $p = .01$; social (prosocial): $r(17) = -0.04$, $p = .87$; social (selfish): $r(6) = -0.21$, $p = .62$ (see online supplemental material for results from the model with both dwell time and final dwell).

Discussion

These results provide substantial support for a domain-general choice process with consistency at the group and individual level. Although individuals differed in the extent to which attention influenced their choices, they demonstrated reliable gaze-choice patterns, suggesting that the method by which people choose between alternatives is consistent across choice contexts. When considering the consistency of attentional influence across domains, it is important to look at the effects of both dwell-time advantage and final dwell location because the aDDM separately predicts both of these effects. For instance, if we had only looked at the final dwell location, we would not have identified the prosocial/selfish divide, as seen in the dwell-time effects.

That being said, the location of the last dwell is very informative. Although it is not purely mechanical (i.e., subjects choose the last-seen option 68%–76% of the time), it does—like subjective value difference and overall dwell-time advantage—significantly predict choice. In the aDDM there is nothing special about the last dwell; it simply corresponds to the time at which a decision barrier is crossed. Because the drift rate is usually biased toward the looked-at option (except when it is much worse than the other option), the decision maker is more likely to choose that option. Additionally, the location of the last dwell is correlated with the dwell-time advantage. That is, the last seen option tends to have been looked at longer than the other option. This also biases choices toward the last-seen option. We have included further analyses of the last-dwell effects in the online supplemental materials. Ultimately, together with the dwell-time effects, the significant correlations in both sets of analyses provide evidence for the consistency of the choice process across tasks at the group and individual levels.

Despite these consistencies, we did observe some discrepancies across the tasks. For instance, the money-risk task showed a slight increase in middle-gaze dwell time as the utility of the outcomes increased. However, this is likely a product of the task design: higher amounts were 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 money-risk task were perfectly correlated with salience, it is possible that the gaze–value relationship that we observed is simply the result of increased salience. The social task used similar stimuli, but subjective value and salience were only weakly correlated because self and other payoffs were negatively correlated. Additionally, the colors of the self and other amounts (red and blue) are less salient than the ultimate brightness/contrast of white on black (Itti, Koch, & Niebur, 1998; Niebur & Koch, 1996) and thus, are likely to have a smaller influence on attention and subsequent choice (Towal et al., 2013). The money-risk task aside, our results are consistent with prior reports that dwell time is not influenced by the subjective value of the stimulus.

The social task is an example of a task in which (some) subjects presumably planned their course of action prior to seeing the alternatives, as evidenced by the large discrepancy between prosocial and selfish subjects in their first-fixation patterns. This distinction between choice processes connects with recent research in the learning literature on model-free versus model-based learning. Specifically, a similar pattern to that observed in our selfish subjects has been identified in model-based—as opposed to model-free—learners, who appear to plan what they will choose before the beginning of the trial (Konovalov & Krajbich, 2016). Like our selfish subjects, they were significantly less influenced by dwell time in their choices and exhibited biased initial fixations. Thus, we now have two examples of non-aDDM choice behavior and

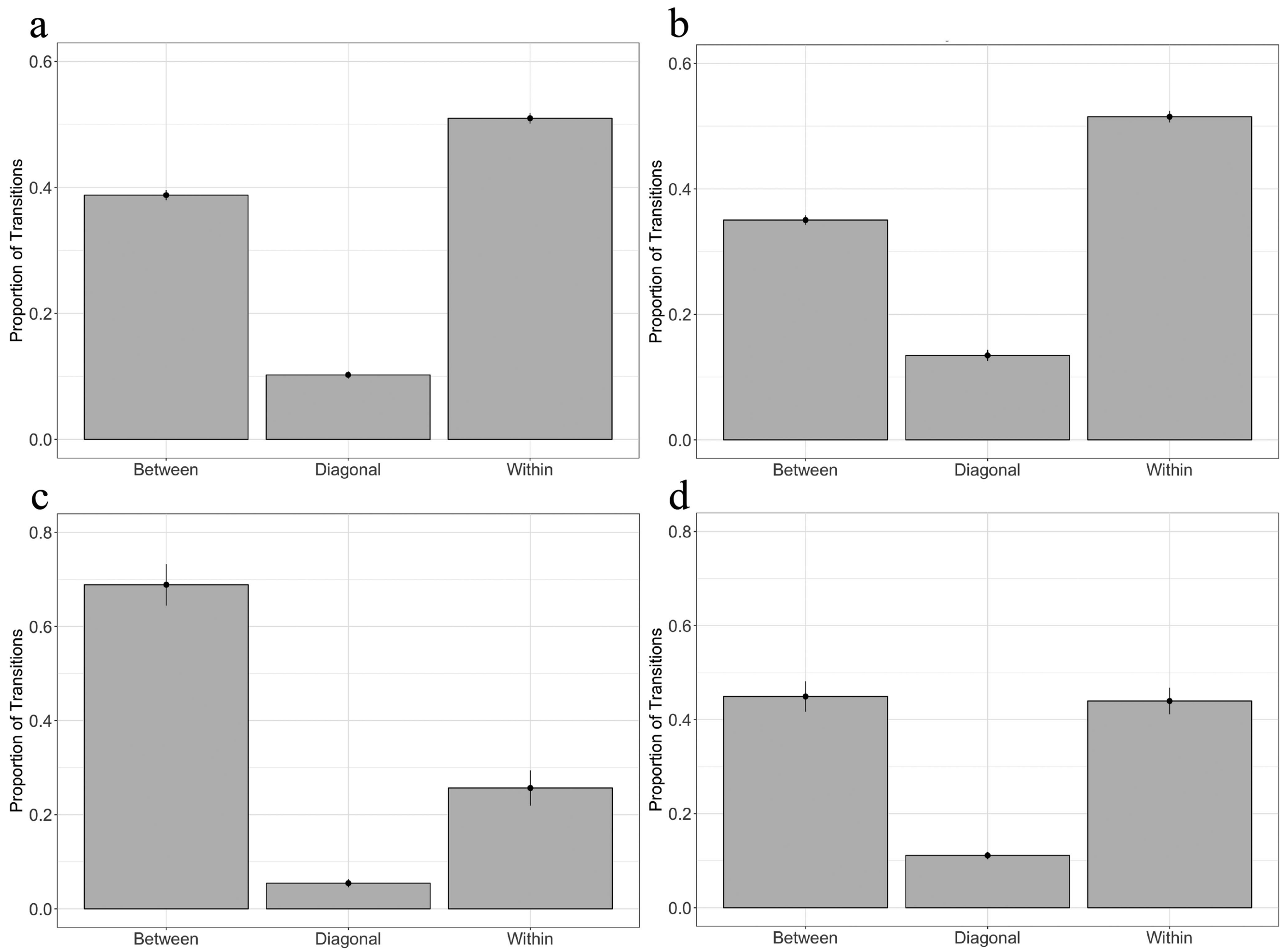

Figure 8. Transitions. Average transition proportions by subject in the (a) food-risk, (b) money-risk, (c) social (selfish), (d) and social (prosocial) tasks. Standard error bars are computed across subjects.

both occurred in situations where subjects could plan their decisions before the options appeared on the screen. Interestingly though, there was a consistency within subjects in the link between final dwell and choice, even for selfish subjects, suggesting that even the selfish subjects were still somewhat influenced by attention in their choices.

Another aspect of individual differences in this study comes from the psychophysical task, which measured the scope of each subject's attention. The initial investigators who developed this task (Robertson et al., 2013) demonstrated that a significant difference in scope exists between subjects with autism and neurotypical controls: people with autism have a narrower scope of attention (referred to as "tunnel vision"). Within each of these groups, however, there is also substantial variation. That is, attentional scope differs along a spectrum. Here we have seen that this measure of covert attention does appear to predict the effect of overt attention on choice. This relationship provides some evidence for the existence of an inherent attentional trait that varies at the individual level and influences choice behavior.

A notable aspect of our study is that we did not manipulate attention in any of the choice tasks: attention is endogenous. Past research (Armel et al., 2008; Lim et al., 2011; Pärnamets et al., 2015) has exogenously manipulated attention in order to establish a causal link between attention and choice. When subjects' gaze is controlled, additional exposure to an option increases the likelihood of choosing that alternative. A consistent causal effect has been demonstrated in choices over foods, consumer goods, and even moral dilemmas.

In the social task, we acknowledge that subjects may have inadvertently associated the colors assigned to the self and other amounts with some semantic meaning. Red and blue have been shown to be interpreted as arousing/happy and relaxing/calming/sad, respectively (Soldat, Sinclair, & Mark, 1997; Stone & English, 1998) and have generally been shown to impact approach/avoidance behavior (Elliot & Maier, 2007). While it is possible that subjects would have been more (or less) prosocial if we had chosen a different color scheme, there is no evidence to suggest that the main intersubject claims that we make in this paper are driven by the colors on the screen.

One limitation of this research is the repeated nature of the decision tasks. People do not often make many sequential choices between food items, lottery tickets, or social divisions of money.

Thus, it is possible that our findings are not directly generalizable to one-shot decisions. An important task for future research will be to investigate the consistency (or inconsistency) across one-shot and repeated decision tasks, especially in the context of eye-tracking.

Another limitation of this research is that these decisions were specifically designed to be nontrivial (i.e., somewhat difficult). Although there is a range in the difficulty of the decisions within each task, we recognize that people make plenty of decisions on a daily basis that are rooted in much stronger preferences/habits such as always buying one's favorite soda in the grocery store. We believe that such "decisions" are better described as goal-directed search processes, rather than stimulus-driven comparison processes. As an example, in this study we observed several purely selfish subjects who appeared to be using a search process to find and select the bigger monetary amount for themselves, disregarding the other subject's earnings.

One more potential limitation to our study is the way in which the outcomes in the money-risk and social tasks were presented. The heights of the boxes directly corresponded to the underlying values of the outcomes. Therefore, in order to choose the option with higher subjective value, subjects had to use the heights of the boxes as proxies for money. It is possible that the use of these boxes, rather than numbers, could have affected the gaze patterns, RTs, and choices. Our aim in using the boxes was to roughly equate the stimuli between the food and box tasks. This concern was fueled by prior work showing that numerical values do not hold attention as long as pictures (Krajbich et al., 2012). An interesting question for future work is to test whether the consistencies we observed in this paper extend to numerical tasks. Based on previous research using numbers to represent risky gambles and social outcomes (Fiedler et al., 2013; Stewart, Hermens, et al., 2015), there is no indication that attention would play a different role in these types of tasks, but a careful quantitative comparison is still lacking.

Ultimately, the recurring theme in this research is the consistency in the connection between gaze and choice. This underlying connectivity has surely been hypothesized, based on the consistent gaze-choice link observed in distinct domains in separate studies (with independent subject samples). However, until now, the stability of attentional influence has not been demonstrated within a subject. Therefore, the current study not only adds evidence for an attention-choice link and verifies the existence of a domain-general decision-making process, but also provides a useful starting point for future investigation into the nuances of attention and choice. In addition to support for consistency of attentional influence, this article also offers one measure (attentional scope) that contributes to individual differences in the effect of gaze on choice.

The way that we interpret our findings is that when making these kinds of decisions (simple, preference-based choices), people do not rely on explicit calculations or decision rules. Instead, they rely on representations of the subjective value of each alternative. These representations dynamically convey information, driving the decision process over time. Our results provide further support for the notion that gaze enhances the representation of the focal alternative, at the expense of the other alternatives. Thus, attention plays a broadly important role in guiding nonrule-based decision making.

Context

When people make decisions, what they look at most usually corresponds to which option they subsequently choose. However, the consistency of the underlying choice process across different decision-making domains, as well as the extent to which attention influences choice, has not yet been established. In this study, we show that people vary in the degree to which attention influences their choices and that for any given person, the magnitude of attentional influence on their decision making is consistent, regardless of the type of decision being made. For instance, people who are highly influenced by where they look during decisions between foods also tend to be highly influenced by their attention in choices between gambles or social distributions of money. Moreover, we find that this individual variability can be identified in a nonchoice "tunnel vision" task, providing further evidence for the stability of this trait. This work builds on the computational framework of the attentional drift diffusion model (aDDM), which was first introduced by Krajbich et al. (2010). Additionally, this research lays the groundwork for ongoing research on the effects of attention on the decision-making process across an even greater variety of contexts.

Statistical Analyses

All reported *t* tests are two-tailed. All reported correlations are Spearman correlations, unless otherwise specified in the text. We conducted all regressions in R (R Core Team, 2015) either at the subject level (for individual-level analyses) or using mixed effects (for group-level analyses) using the R package lme4. If a mixed-effects regression did not converge, we used the R package brms (Bayesian regression models using Stan). The code for these analyses is available upon request.

Data Availability

The data that support the findings of this study will be made available at https://osf.io/g7cv6/?view_only=2669d8f3983d4442952a52c5de5814f7.

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