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The spillover effects of attentional learning on value-based choice

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ABSTRACT

What role does attention play in decision-making? Prior research has demonstrated a link between visual attention and value-based choice, but the direction of causality is still unclear. Here we aimed to demonstrate that attention has a causal influence on choice. We tested whether spatially biasing attention in a visual search task would produce choice biases in a later choice task. We ran four experiments where the search target was more likely to appear on one "rich" side of the screen. In the subsequent choice tasks, participants were more likely to choose items appearing on the rich side and the average choice bias depended on how well participants learned the regularity in the search task. Additionally, eye-tracking data revealed a first-fixation bias toward the rich side, which in turn influenced choices. Taken together, these results provide novel support for a causal effect of attention on choice.

1. Introduction

One of the most fundamental challenges we face as humans is to efficiently process the information that we are surrounded by. Attention allows us to prioritize behaviorally relevant information while ignoring irrelevant information (Chun, Golomb, & Turk-Browne, 2011; Egeth & Yantis, 1997). An abundance of research suggests that attention interacts with essentially every known cognitive function (Baddeley, Lewis, Eldridge, & Thomson, 1984; Chun & Johnson, 2011; Chun et al., 2011; Hillyard et al., 1998; Hillyard, Vogel, & Luck, 1998; Kane & Engle, 2000; Woldorff et al., 1993). Attention is also thought to play a critical role in decision-making, influencing which aspects of a choice problem are evaluated from moment to moment (Roe, Busemeyer, & Townsend, 2001), though it may also limit our ability to simultaneously compare options (Krajbich, Armel, & Rangel, 2010). For instance, when deciding what to eat for lunch, we may imagine at one moment what it would be like to eat a cheeseburger while imagining at another moment what it would be like to eat a salad. However, it is still not well understood whether attention causally determines the outcomes of decisions or merely reflects the emerging preference.

Many models of the decision process assume serial processing of information, including seminal models such as satisficing (Simon, 1955), elimination-by-aspects (Tversky, 1972), decision field theory (Busemeyer & Townsend, 1993; Diederich, 1997; Roe et al., 2001), fast-and-frugal heuristics (Gigerenzer & Goldstein, 1999), and query theory (Weber et al., 2007). In these models, attention to attributes or alternatives varies over time, influencing the extent to which they affect the final decision.

In many of these models, attention is thought to be attracted to more important or predictive attributes/alternatives (Aschenbrenner, Albert, & Schmalhofer, 1984; Bordalo, Gennaioli, & Shleifer, 2012; Cassey, Evens, Bogacz, Marshall, & Ludwig, 2013; Khodadadi, Fakhari, & Busemeyer, 2017; Wallsten & Barton, 1982). At the same time, other (potentially irrelevant) factors such as visual saliency (Mormann, Navalpakkam, Koch, & Rangel, 2012), even when made salient after the decision process has begun (Bear & Bloom, 2016), or emotional content (Vuilleumier, 2015) might also attract attention and thus affect the decision outcome.

In a related literature, perceptual fluency, or the ease with which one perceives information, is also thought to influence preferences. Prior studies have demonstrated that positive affective judgments are increased by prior exposure (Zajonc, 1968), primes that facilitate perception (Winkielman & Cacioppo, 2001), and higher contrast (Reber, Winkielman, & Schwarz, 1998). Previously ignored stimuli are also devalued (Raymond, Fenske, & Tavassoli, 2003), though it has been argued that this is more likely due to attentional inhibition than perceptual fluency (Fenske & Raymond, 2006).

To more systematically investigate the link between attention and decision making, some researchers have employed eye tracking. For example, Shimojo and colleagues showed that, over time, gaze tends to shift towards the option that is eventually chosen; a phenomenon referred to as the *gaze cascade effect* (Shimojo, Simion, Shimojo, &

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Scheier, 2003). Because eye position is a reliable overt measure of attentional allocation (Corbetta et al., 1998; Hoffman & Subramaniam, 1995), this effect provides an important demonstration of the interplay between choice and attention.

To model the relationship between attention and choice, Krajbich et al. (2010) proposed an attentional drift diffusion model (aDDM) in which evidence for each option is accumulated and compared over time until one item gains sufficiently more evidence than the other. The key, novel feature of this model was that evidence is accumulated more quickly for an item when it is being looked at than when it is not. Using a binary food choice task, the authors demonstrated that the model could quantitatively capture many complex relationships between choices, response times, and gaze data. In particular, it was able to predict the gaze cascade effect without assuming that attention is drawn to the emerging favorite. The aDDM itself is agnostic about the direction of causality, but other features of the data suggest a causal link from attention to choice. For instance, the authors found no correlation between gaze time and independently measured valuations of the items, but they did find that gaze time was predictive of choice.

Other studies have also implicated an important role for eye movements in choice (Ashby, Dickert, & Glöckner, 2012; Ashby, Jekel, Dickert, & Glöckner, 2016; Cavanagh, Wiecki, Kochar, & Frank, 2014; Fiedler & Glöckner, 2012; Fiedler, Glöckner, Nicklisch, & Dickert, 2013; Fisher, 2017; Folke, Jacobsen, Fleming, & De Martino, 2016; Franco-Watkins & Johnson, 2011; Glaholt & Reingold, 2011; Isham & Geng, 2013; Janiszewski, Kuo, & Tavassoli, 2013; Kim, Seligman, & Kable, 2012; Konovalov & Krajbich, 2016; Kovach, Sutterer, Rushia, Teriakidis, & Jenison, 2014; Krajbich & Rangel, 2011; Krajbich, Lu, Camerer, & Rangel, 2012; Mullett & Stewart, 2016; Noguchi & Stewart, 2014; Orquin & Mueller Loose, 2013; Pärnamets, Johansson, Gidlöf, & Wallin, 2016; Polonio, Di Guida, & Coricelli, 2015; Reutskaja, Nagel, Camerer, & Rangel, 2011; Russo & Leclerc, 1994; Shi, Wedel, & Pieters, 2012; Stewart, Hermens, & Matthews, 2015; Tavares, Perona, & Rangel, 2017; Vaidya & Fellows, 2015; Wang, Spezio, & Camerer, 2009; Willemsen, Böckenholt, & Johnson, 2011). Still, these studies have focused on correlations between visual attention and choices, so they cannot fully address the issue of causality, i.e. whether attention is driving preference or preference is driving attention.

To address this problem, other studies have attempted to influence attention exogenously. Armel, Beaumel, and Rangel (2008) displayed one option at a time and thus were able to manipulate relative exposure times. Participants were more likely to pick the item that appeared on the screen for a longer duration. Lim, O'Doherty, and Rangel (2011) used an analogous paradigm, but kept both choice items on the screen and directed gaze using exogenous cueing. Again, items receiving more attention were more likely to be chosen.

Another set of studies attempted to physically alter the salience properties of the stimuli in order to more subtly influence attention. In the first study (Mormann et al., 2012) the researchers increased the brightness of one of the items so that it would be more salient than the other. This manipulation did increase choices for the more salient item, with the strongest effects at shorter presentation durations (on the order of 100 ms). In a follow-up paper, Towal, Mormann, and Koch (2013) introduced a choice model which takes into account the salience of an item in relation to its surroundings. They found that a model accounting for both salience and value of each item was best able to predict decisions. Still other studies have shown that one can bias choice by prompting participants to decide when their attention has been particularly devoted to one option over the other (Pärnamets et al., 2015), or by making options in one location more valuable than in other locations (Colas & Lu, 2017).

While these studies have made important strides in establishing the causal link between attention and choice, they utilize techniques that directly interfere with the natural choice process (Armel et al., 2008; Lim et al., 2011; Pärnamets et al., 2015), alter the properties of the choice options (Mormann et al., 2012; Towal et al., 2013), or manipulate participants' expectations (Colas & Lu, 2017). Thus, we cannot rule out alternative explanations for the results.

The attention literature has provided several techniques for experimentally manipulating attention. For instance, in *probability cueing*, targets are presented more frequently in one spatial location compared to others (either a specific location or a general region of the display). This has been shown to influence attentional allocation through shorter reaction times (RT) and eye movements directed towards targets appearing in more probable locations, even after the probability manipulation has ceased (Druker & Anderson, 2010; Geng & Behrmann, 2005; Jiang, Swallow, & Rosenbaum, 2013; Jiang, Won, & Swallow, 2014).

Here, we aimed to use this attentional learning technique to provide definitive evidence that attention influences choice. We did so by introducing attentional biases without altering the presented choice stimuli in any way, and without unnaturally forcing eye movements or decision times. Instead, we used a separate attentional learning task to induce a spatial bias in attention, and then tested whether that spatial bias would spill over into a later, independent choice task.

In Experiment 1, we aimed to provide evidence that attention causally influences choice by using probability cueing to induce a spatial bias in attention. We hypothesized that this spatial bias would spill over into a later, independent choice task where participants chose which of two food items they would prefer to eat. Moreover, we also hypothesized that the extent of each individual's attentional learning, as captured by the RT-difference between spatial locations, would predict the size of their subsequent choice bias. In two additional experiments (Experiments 2 & 3) we investigated whether these spatial biases could be induced or reversed in a second set of food choices following the first food-choice task. These experiments probed the malleability and limits of attentional learning while also controlling for potential baseline spatial biases. Finally, in Experiment 4 we collected eye-tracking data to directly establish that probability cueing affected subsequent eye-movements, and therefore choice.

2. Experiment 1

2.1. Materials and methods

2.1.1. Participants

42 undergraduate students at The Ohio State University participated in the initial experiment (Gwinn, Krajbich, & Leber, 2018a). One participant failed to complete the binary choice task due to insufficient positively rated items. One other participant was excluded due to performing significantly below chance during the visual search task. Participants earned a show-up fee of $7. In addition to this, participants earned an average of $7.59 during the probability manipulation as well as the food item from one randomly selected choice trial.

2.1.2. Apparatus

All images were created and displayed using Matlab (Mathworks) in conjunction with Psychtoolbox (Brainard, 1997). Participants sat approximately 101 cm away from the screen and used a standard U.S. keyboard to indicate their responses.

2.1.3. Obtaining value

The first task that participants completed was a rating task (Fig. 1A). Participants saw an individual image of each of the snack items (91 in total for Experiment 1) and a rating scale from −10 to +10 in increments of one. Participants used the right and left arrow keys to move the slider on this number scale to indicate their desired rating, at which point they pressed "enter" on the keyboard to confirm. A rating of "−10" indicated that the item was very disliked, "+10" indicated that the item was very liked, and "0" indicated that the item was neither liked nor disliked. Items were presented in a random order and transitioned immediately between ratings. Food images were procured from a database made available by the Rangel lab (Plassmann, O'Doherty, &

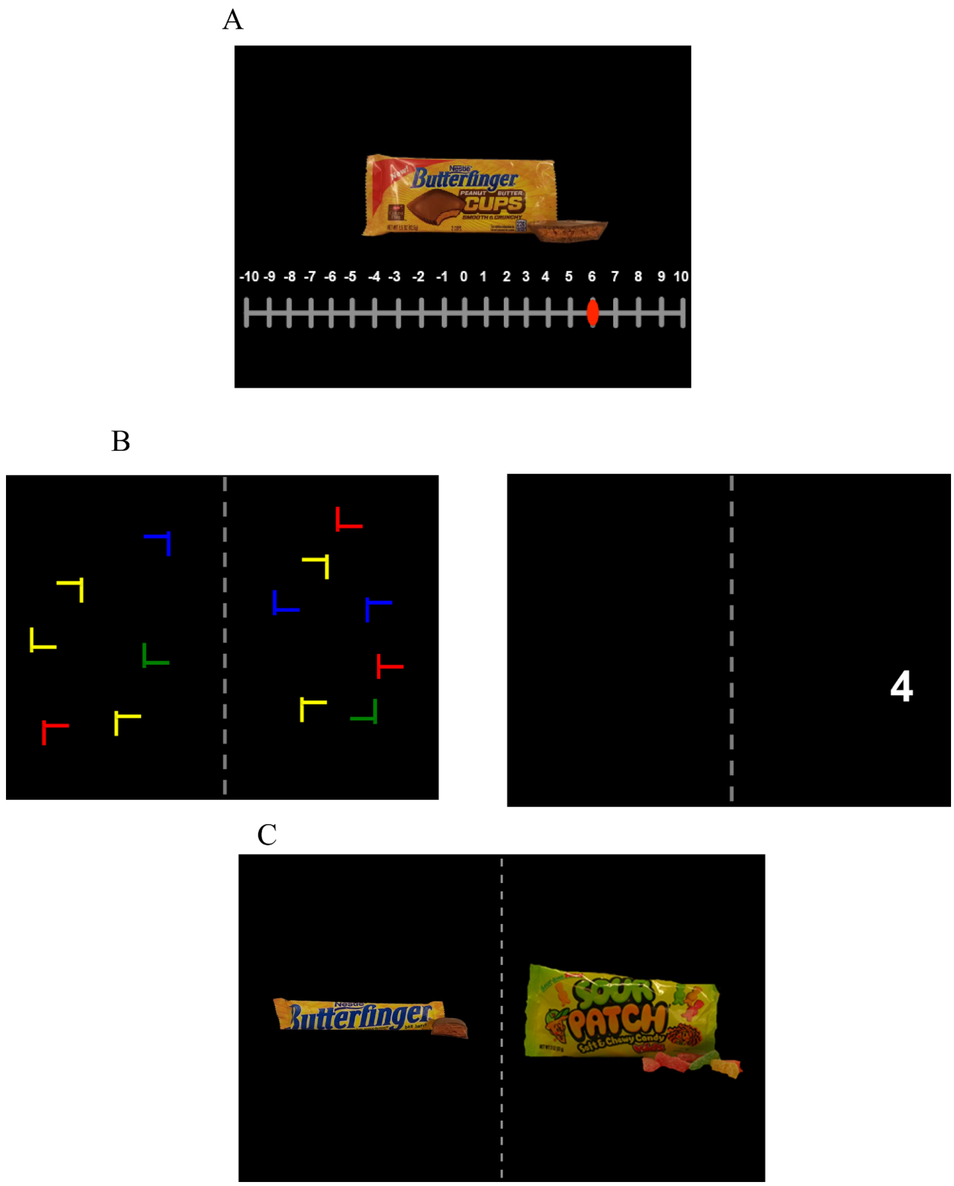

Fig. 1. Experiment components (a) Rating task: Participants rated each item on a scale from −10 to +10 based on how much they would like to eat the item. (b) Visual search task: participants had 8 s to locate a rotated T among rotated Ls and indicate whether the T was rotated 90° to the left or to the right. A correct answer was given a reward of 4 points (c) Binary food-choice task: Participants indicated which of two food items they preferred.

Rangel, 2007) and supplemented with additional images.

2.1.4. Training – attentional biasing

In order to manipulate attentional allocation, we used a visual search task (Fig. 1B). In this task, we presented participants with 12 rotated L's (distractors) and one T (target) which was rotated 90° left or right. The task was to report whether the target T was rotated to the left (press the left arrow key) or to the right (press the right arrow key). The key attentional manipulation was that the "rich" side of the display was more likely to contain the target (75%) than the other "sparse" side (25%).

At the beginning of each trial, participants saw a fixation cross at the center of the screen, which lasted for 1 s. They were instructed to look at the fixation cross until the search display appeared.

In the search display, T's and L's were matched for size, each letter subtending 0.72° visual angle and appearing at a minimum eccentricity of 1.20° from the center of the screen and a maximum eccentricity of 7.23° from the center of the screen. Each T and L was randomly and independently colored blue, red, yellow, or green. Each L was randomly rotated by 90 or 270° and randomly flipped over the horizontal axis or not. To increase search difficulty, we slightly offset the horizontal line segment of each L to make it more similar to a sideways T. A dashed grey line vertically bisected the screen, so as to clearly separate the left from the right, in order to encourage learning. The search display was presented until response or for 8 s, whichever came first.

Each participant was assigned a different rich side of the display; 47.5% of the participants had the rich side on the left. While we did not tell participants about the probability manipulation, prior research indicates that most participants do not become aware of it (Druker & Anderson, 2010; Geng & Behrmann, 2002; Jiang, Swallow, Rosenbaum, & Herzig, 2013).

Participants completed 200 search trials, with a break halfway through. Accurate responses to targets yielded a reward of 4 points. Immediately upon responding, participants were shown how many points they had earned on that trial. The total number of points earned was also displayed at the resting point 100 trials into the task and was displayed again at the end of the task. Points were translated to dollars at the rate of 100 points per dollar. Maximum earnings were $8.

2.1.5. Test – choice

To test the effects of our attention manipulation we used a binary food-choice task. In each trial, participants saw two food items on the screen and were told to choose the item that they preferred. These choices were incentivized. That is, a trial was drawn at random at the end of the study, and the participant received the item they had chosen on that trial. If the randomly selected food item was not in stock, another trial was drawn at random until we were able to provide the participant with a food item they had chosen.

Choice trials were created by selecting every possible pair of items with an absolute rating difference of 1 or less. Pairs were then randomly selected from this master list, attempting to minimize the number of times any one item was seen. On average, the maximum number of times any one item was seen was 5.9.

At the beginning of each trial, participants saw a fixation cross at the center of the screen, which lasted for 1 s. They were instructed to look at the fixation cross until the choice screen appeared.

As in the search task (Section 2.1.4), a dashed grey line once again appeared down the center of the screen in order to define the left from the right side. Two food items appeared on the screen, each subtending 6.94° and appearing 1.34° from the center (Fig. 1C). Participants chose their preferred food item using the left and right arrow keys. Food items remained on the screen until a choice was made. Once a choice was made, a blue outline square appeared around the chosen item for 500 ms.

Participants completed 130 binary choice trials. We did not include any items that received a rating less than 0 (we did not mention this to the participants). Additionally, we only used pairs of items with a maximum rating difference of 1; we did this to focus on difficult choices, in which the effects of attention would be most noticeable. The percentage of trials with a rating difference of 0 was 39–44% in all four experiments.

2.2. Results

In this study, the target during the search task was more likely to appear on the rich side (75%) than the sparse side (25%), which has been shown to increase attentional allocation to the rich side (Geng & Behrmann, 2002). We hypothesized that this spatial prioritization of attention toward the rich side would then carry over into the food choice task, biasing participants' choices towards the rich side.

2.2.1. Training

First, we analyzed behavior during the visual search task. Mean accuracy was 91.32% (s.e. = 2.7%) and did not differ between targets on the rich vs. sparse side (mean difference = 0.40%, t = 0.48, 95% CI [−1.30%, 2.09%], d = 0.02). RTs were significantly shorter for targets appearing on the rich vs. sparse side (mean difference = 475 ms, t = 6.14, 95% CI [318 ms, 631 ms], d = 0.85) (Fig. 2A). This replicated previous probability cueing results, demonstrating that the participants learned to attentionally prioritize the rich side of the display.

2.2.2. Test – main effect

We next investigated whether there was an effect of the attentional manipulation on the food choice task. Because we were interested in the effect of the attentional manipulation, we excluded participants who did not score significantly above chance during the visual search task (N = 2); we reasoned that these individuals had not learned the task and thus would not display biases induced by the manipulation.

We used a mixed-effects logistic regression with the probability of choosing the food item from the rich side as a function of the value difference between the rich item and the sparse item (i.e. the item on the rich side minus the item on the sparse side), with random effects for all regressors. In this regression, the value-difference variable indicates how well participants' choices aligned with their earlier ratings, and the intercept indicates any bias toward choosing the rich item or the sparse item. Specifically, a positive intercept indicates a bias toward choosing the rich item.

The effect of value difference was highly significant (β = 0.42, 95% CI [0.33, 0.51]), indicating that participants' choices were indeed correlated with their earlier liking ratings. Note that across all experiments, this regressor was always highly significant and so for brevity we omit reporting it in subsequent results sections (although full regression results for all analyses are available in the Supplementary material).

In line with our hypothesis, we found a positive intercept (β = 0.07, 95% CI [0.02, 0.13]). This indicates that participants' decisions were biased toward the rich side of the display (Table S1).

2.2.3. Test – establishing the role of attention

In order to establish that our observed choice bias was due to attention and not other possible factors, we sought to test whether there was a correlation between the degree of attentional learning during the search task and the size of the choice bias during the decision task. For this we used the RT difference between the sparse and rich sides during training.

It was also suggested to us that accuracy during the search task might be predictive of the subsequent choice bias, as it might serve as an alternative measure of learning in the search task. We also suspected that overall value, that is the sum of the ratings for the left and right items, might affect the choice bias. This last prediction comes from a subtle feature of the aDDM. In the model, evidence for an unattended item is discounted by a factor of θ. This means that items with higher values are discounted more in absolute terms, leading to a larger effect of attention on choice.

To best characterize which, if any, of these variables were important in determining final choice, we ran several mixed-effects logistic regressions with all possible combinations of these three variables plus rating difference and intercept and used the Akaike Information Criterion (AIC) to compare them (see Table S2). Because we later conducted a meta-analysis across all four experiments, the goal here was simply to rule out variables/models that provided clearly worse fits to the data. Therefore, here (and later for Experiments 2 & 3) we report the results from the most complex model whose AIC fell within 2 of the best-fitting model (Posada & Buckley, 2004). Later, in the meta-analysis, we focus exclusively on the best-fitting model.

For these analyses we ran the regressions including the participants who did not score significantly above chance on the search task, since they essentially serve as control participants that did not learn the attention manipulation. In other words, it helps to compare participants who did not learn the attentional manipulation to those who did (but see Table S3 for results without these inclusions). We continued to exclude participants who scored significantly below chance (N = 1), as these participants seem to have learned the manipulation but were not following directions.

Our AIC rule selected the model that included both RT difference and accuracy, in addition to rating difference and intercept. RT difference and accuracy, both proxies for the degree of attentional learning, positively predicted choosing from the rich side (β = 0.11, 95% CI [−0.004, 0.22] and β = 0.64, 95% CI [0.21, 1.06] respectively) though RT difference was not quite significant. In other words, participants who displayed bigger learning effects in the search task were more biased in their later food choices (Fig. 3A).

After accounting for the degree of attentional learning, we should not expect any remaining choice bias. Indeed, this more complex model yielded a negative intercept (β = −0.58, 95% CI [−0.99, −0.18]). Because the accuracy variable was coded from 0 to 100%, with 50% being chance level, the negative intercept in this complex model simply indicates that, in theory, a participant with 0% accuracy would be biased towards choosing from the poor side. In other words, this merely confirms the effect of accuracy on choosing from the rich side.

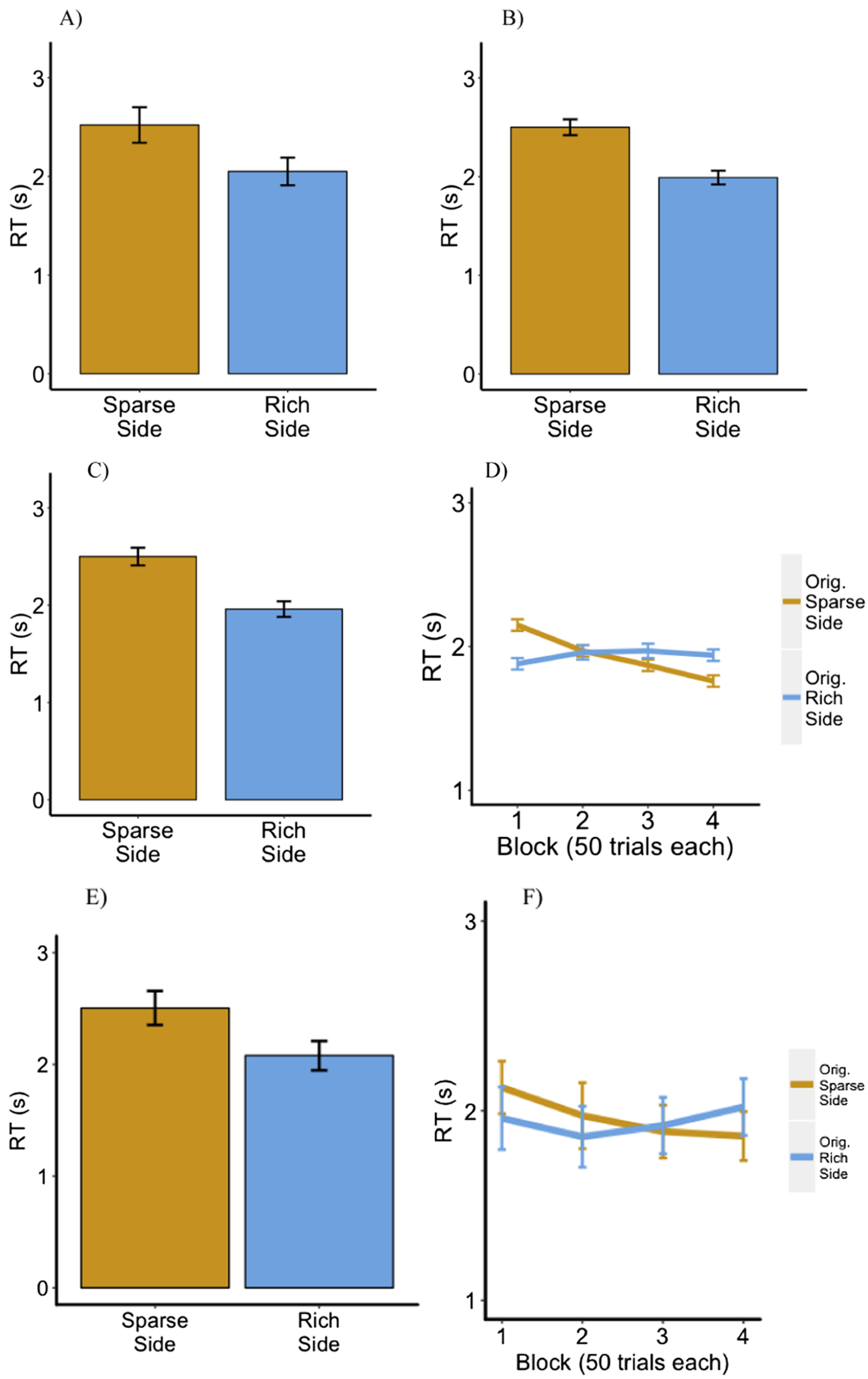

Fig. 2. Search task results. Reaction times (RT) from the search task in (a) Experiment 1 (b) Experiment 2 (c) Experiment 3, first search task (d) Experiment 3, second search task, separated into blocks of 50 trials (e) Experiment 4, first search task (f) Experiment 4, second search task, separated into blocks of 50 trials (g) Experiment 4, first search task initial fixations (h) Experiment 4, second search task initial fixations by blocks of 50 trials. Rich and sparse refer to the assignment in the original search task. In (d), (f), and (h) the original sparse side (orange) is now the rich side, and so its RTs, as well as first fixations to the original rich side, decline as participants learn the new assignment. Bars indicate 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Experiment 2

In this pre-registered experiment, we sought to replicate our first experiment and test whether the attentional bias could be detected relative to participants' baseline behavior on a choice task prior to the search task. It was unclear whether the attentional manipulation would still succeed in this context, since participants might become less susceptible to the manipulation after already going through the choice task. To preview the results, we do not replicate the choice bias, though the effect is in the predicted direction. We do however observe some new effects when comparing pre- and post-training choices.

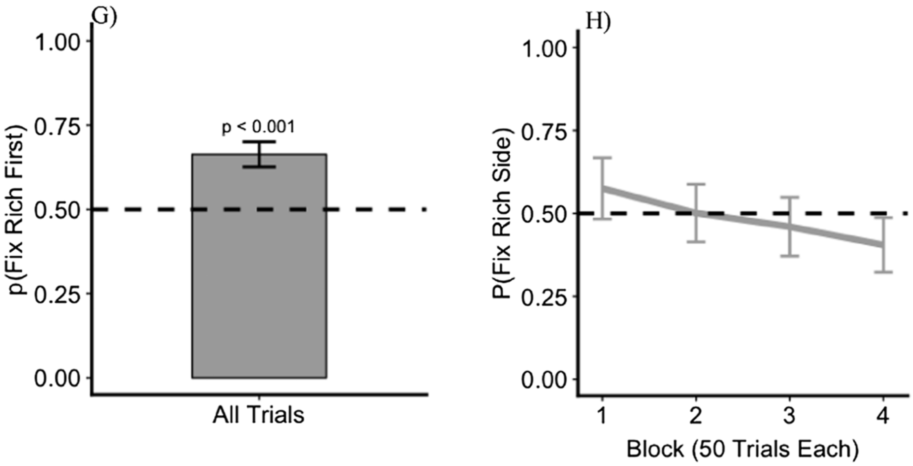

Fig. 2. (*continued*)

3.1. Methods

3.1.1. Participants

As detailed in the pre-registration of this study, we used a power analysis to determine that we should use a sample size of at least 135 participants to achieve power of 0.9 (Gwinn, Krajbich, & Leber, 2016, February 24). We ran these experiments in a 30-person experimental lab at the Ohio State University and our stopping rule was to invite full sessions until we had run 135 participants. We ended up with 163 undergraduate students. Nine participants were excluded for having too few positively rated food items. An additional 3 were excluded due to computer crashes. One final participant was excluded from all analyses for scoring significantly below chance on the search task. Participants earned an average of $7.89 during the search task (Gwinn et al., 2018a).

3.1.2. Task

The procedure for this experiment was the same as Experiment 1 (Section 2.1.2), except as noted below.

The main difference from Experiment 1 was that between the food rating task and the visual search task, participants completed 130 trials of the binary choice task. This was done to establish participants' baseline behavior on the choice task. In the second, manipulated choice task (also 130 trials), we made sure to not repeat any of the pairings from the first choice task. To accommodate these additional choice trials, we expanded the number of food items to 147. 49% of the non-excluded participants had their rich side on the left. On average, the maximum number of times any one item was seen was 6.81.

3.2. Results

3.2.1. Training

As in Experiment 1, we first analyzed the results from the search task (Section 2.2.1). Average accuracy was 96.28% (s.e. = 0.65%) and was greater for targets on the rich side (mean accuracy difference = 0.99%, t = 3.35, 95% CI [0.41%, 1.60%], $d = 0.12$). As expected, RTs to items appearing on the rich side were significantly shorter (mean difference = 517 ms, t = 13.99, 95% CI [444 ms, 590 ms], $d = 0.97$), replicating the probability-cueing effect (Fig. 2B). This again indicates that participants learned the attentional manipulation.

3.2.2. Test – main effect

Next we wanted to know if the attentional manipulation influenced choices. To do this we first looked at only the second choice task, which occurred after the attentional manipulation. This analysis simply replicated that from the first experiment. As before, we ran a mixed-effects logistic regression of the probability of choosing the rich item, controlling for the rating difference between the items on the rich and sparse sides. In contrast to Experiment 1 (Section 2.2.2) the intercept was not significant ($\beta = 0.011$, 95% CI [−0.03, 0.05]) (Table S4). Hence, there was no significant choice bias in this study.

3.2.3. Test – establishing the role of attention

To investigate further, we again expanded our regression models to include RT difference, accuracy, and overall value as independent variables. Here the AIC-selected model included only RT difference as an additional predictor (Table S5). RT difference did not significantly predict choosing from the rich side, though the effect was in the predicted direction ($\beta = 0.06$, 95% CI [−0.02, 0.14]) (Fig. 3B). Again, after accounting for the degree of attentional learning, we expect and find no remaining choice bias ($\beta = -0.02$, 95% CI [−0.07, 0.04]).

3.2.4. Test – comparing pre-training and post-training

In accordance with our registration for this study, we ran a mixed-effects logistic regression of the probability of choosing the rich side on every combination of the following parameters: rating difference, RT difference, accuracy, overall value, and treatment (a binary variable coding for whether choices occurred before (0) or after (1) the search task), as well as models including two and three way interactions with the treatment variable.

Out of these models, the regression with rating difference, overall value, treatment, and the interaction between treatment and rating difference produced the best fit (Table S6). There was no significant coefficient on the intercept ($\beta = 0.032$, 95% CI [−0.01, 0.08]), overall value ($\beta = -0.003$, 95% CI [−0.006, 0.001]), or on treatment ($\beta = 0.004$, 95% CI [−0.04, 0.05]). However, there was a significant negative interaction between treatment and rating difference ($\beta = -0.15$, 95% CI [−0.20, −0.09]), indicating that after the search task, participants were less likely to choose the higher rated foods.

This last result suggests that our attentional manipulation did have an effect on participants' food choices, though not in the exact same way as in Experiment 1. One concern is that the increased delay between the rating task and the second choice task (and possibly fatigue) could be responsible for the less consistent choices. To test these competing hypotheses we again included the RT-difference variable as a way to capture the amount of learning during the search task. We reasoned that if the RT-difference variable modulated the effect of the treatment on choice consistency, then that would support the hypothesis that the change in behavior was due to the treatment and not due to time delay or fatigue.

Indeed, in this analysis we see that there was a significant, three-way, negative interaction between rating difference, RT difference, and treatment ($\beta = -0.16$, 95% CI [−0.30, −0.02]). This means that after

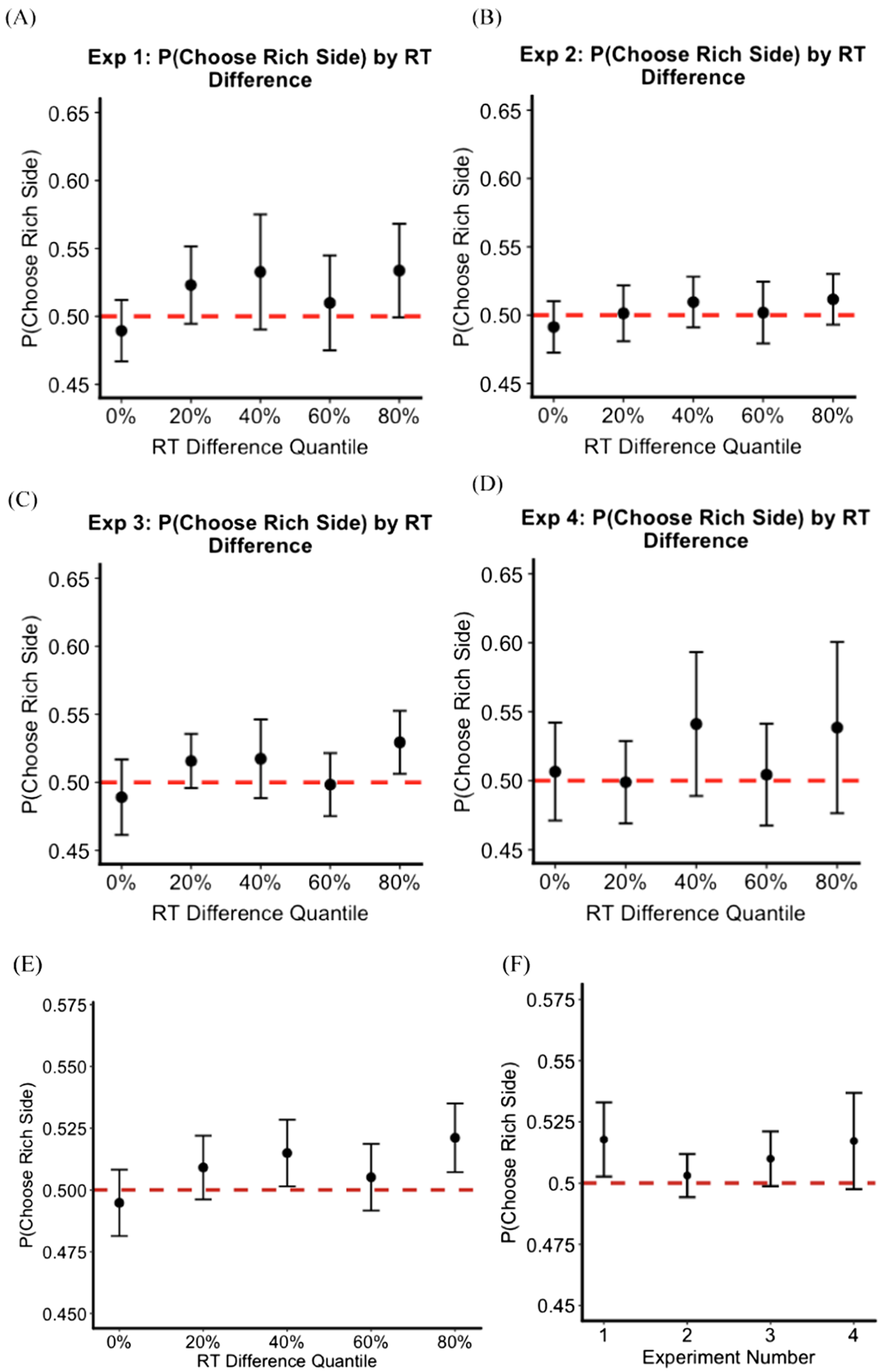

Fig. 3. Choice bias as a function of attention bias. (a–d) Mean probability of choosing the food item from the rich side of the display, as a function of the RT difference from the search task. Subjects were split into five even-sized groups (quintiles) within each experiment. (e) Subjects were then combined across experiments. In other words, the far-right bin represents the most attentionally biased 20% of the subjects from Experiment 1, 20% of the subjects from Experiment 2, 20% of the subjects from Experiment 3, and 20% of the subjects from Experiment 4. We observe a fairly consistent increase in the choice bias as the RT difference increased. (f) Probability of choosing from the rich side for each study. Bars indicate 95% confidence intervals.

the search task, participants who displayed a bigger attentional bias were less likely to choose the higher rated items. All other coefficients and interactions were non-significant (intercept: $\beta = 0.01$, 95% CI [−0.05, 0.07]; treatment: $\beta = -0.03$, 95% CI [−0.09, 0.03]; RT difference: $\beta = -0.01$, 95% CI [−0.09, 0.07]; rating difference x RT difference: $\beta = 0.04$, 95% CI [−0.08, 0.16]; treatment x RT difference: $\beta = 0.07$, 95% CI [−0.03, 0.17]; treatment x rating difference: $\beta = -0.06$, 95% CI [−0.14, 0.02]).

4. Experiment 3

In the third experiment we again sought to replicate Experiment 1 while attempting to erase or reverse the attentional bias within participant. We began with a closer replication of Experiment 1, including the search task, followed by a choice task, but then participants completed a second search task in which the spatial manipulation was reversed, followed again by a second choice task. We anticipated a replication of the choice bias found in Experiment 1 on the first choice task. Furthermore, we hypothesized that the bias in the second choice task would disappear, or possibly reverse, relative to the bias in the first choice task.

4.1. Methods

4.1.1. Participants

126 undergraduate students at the Ohio State University participated in this study, as outlined in a second pre-registration (Gwinn, Krajbich, & Leber, 2016, March 14). Two participants were excluded from the analyses for having an insufficient number of positively rated items. Two additional participants experienced computer crashes and were unable to finish the study.

To compensate for the longer experiment, participants in this experiment earned a show-up fee of $5 for the study in addition to an average of $15.79 during the search tasks (as well as one food item from a randomly selected trial) (Gwinn et al., 2018a).

4.1.2. Task order

The procedure for this experiment was the same as Experiment 1 (Section 2.1.2), except as noted below.

The main difference from Experiment 1 was that after completing the rating task, the search task and then the 130 trials of the choice task, participants then completed another 200 trials of the search task with the rich side reversed from before, so that if it originally was on the left, it would now be on the right, and vice-versa. This has been shown to eliminate attentional bias effects (Jiang, Swallow, Rosenbaum, et al., 2013). This was followed by another 130 trials of the choice task. As in Experiment 2, we made sure to not repeat any of the pairings from the first choice task and we used 147 food items. In this experiment exactly 50% of the participants had their rich side on the left during the first search task. On average, the maximum number of times any one item was seen was 8.2.

4.2. Results

4.2.1. Training

As before, we describe the results from the search tasks first. Mean accuracy during the first search task was 96.66% (s.e. = 0.68%) and was significantly higher on the rich side (mean accuracy difference = 0.68%, t = 2.93, 95% CI [0.22%, 1.14%], d = 0.09), unlike Experiment 1 (Section 2.2.1) but replicating Experiment 2 (Section 3.2.1). As before, RTs showed a significant difference between sparse and rich sides (mean difference = 492 ms, t = 10.74, 95% CI [402 ms, 583 ms], d = 0.98) (Fig. 2C).

In the second search task, accuracy was 97.57% (s.e. = 0.72%) and was not significantly different between sides (mean accuracy difference = 0.26%, t = 1.35, 95% CI [−0.12%, 0.63%], d = 0.03). For simplicity we will always refer to the rich and sparse sides based on how they were assigned in the first search task. In other words, for one participant the “rich” side label would be the left side in both the first and second search tasks, despite the actual reversal. As predicted, the RT difference between the sparse and rich sides disappeared (mean difference = 1.91 ms, t = 0.042, 95% CI [−86 ms, 90 ms], d = 0). For a more fine-grained look at the extinction of the RT effect we examined behavior in the second search task in blocks of 50 trials. Participants remained significantly faster at detecting targets on the rich side for the first 50 trials (mean difference = 266 ms, t = 5.06, 95% CI [162 ms, 370 ms], d = 0.54), were not significantly faster in either direction for the next two blocks of 50 trials (mean difference = 10 ms, −98 ms, t = 0.17, −1.74, 95% CI [−108 ms, 128 ms], [−210 ms, 14 ms], d = 0.02, −0.2), and were significantly faster for targets on the sparse side for the last block of 50 trials, (mean difference = −173 ms, t = −3.84, 95% CI [−263 ms, −84 ms], d = −0.37) (Fig. 2D).

4.2.2. Test – main effect

Next we turned to the choice data. Looking only at the first 130 choice trials, and using data taken from only the first search task, we ran the same mixed-effects logistic regression, looking at the probability of choosing from the rich side based on rating difference. As before, anyone with a search accuracy not significantly above chance was excluded (N = 3). Here we found that the intercept was marginally significant (β = 0.04, 95% CI [−0.005, 0.09]) (Table S7).

4.2.3. Test – establishing the role of attention

To investigate further, we again expanded our regression models to include RT difference, accuracy, and overall value as predictors. As in the prior experiments, the three excluded participants were re-included in this analysis. Here the AIC-selected model included overall value and RT difference as additional predictors (Table S8). RT difference, our measure of attention, was in the correct direction but not significant (β = 0.06, 95% CI [−0.03, 0.15]) (Fig. 3C). Overall value was marginally significant (β = 0.005, 95% CI [−0.0003, 0.01]). Again, accounting for the degree of attentional learning, we expect and find no remaining choice bias (β = −0.04, 95% CI [−0.11, 0.04]).

4.2.4. Test – post extinction

We next investigated how these same regressions differed after the reversed search task. First, we ran the simple regression of choosing the original rich side on rating difference, again excluding those participants who did not perform above chance on the search task (N = 3). The bias to choose the original rich side disappeared (in fact slightly changed sign) (intercept β = −0.005, 95% CI [−0.066, 0.056]) (Table S9).

Additional regressions including RT-difference from the two search tasks paint a complex picture and are described in detail in the supplements. Also, direct comparisons between the two choice tasks failed to reveal any significant differences (see supplements and Tables S10 and S11).

5. Experiment 4

In the fourth experiment, we collected eye-tracking data to test whether the effects we had found in the prior experiments were indeed due to attention. We replicated the procedure for Experiment 3 (Section 4.1.2), testing whether the probability cueing task would bias participants' first fixations or dwell times towards the rich side of the display.

5.1. Methods

5.1.1. Participants

43 undergraduate students at The Ohio State University participated in this study. Eight participants were excluded for having an insufficient number of positively rated items, leaving us with 35 valid participants, as outlined in our pre-registration (Gwinn, Krajbich, & Leber, 2017, August 11).

As in Experiment 3, participants in this experiment earned a show-up fee of $5 for the study in addition to an average of $15.88 during the search tasks (as well as one food item from a randomly selected trial) (Gwinn, Krajbich, & Leber, 2018b).

5.1.2. Task order

This study was identical to Experiment 3 (Section 4.1.2) in task order, with the addition of eye-tracking during both search and choice tasks. Participants' left-eye movements 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 participant. We used a chinrest provided by the manufacturer to minimize head movement. All stimuli were presented on an LCD monitor (24′ XL2420TE, BenQ), located 79 cm in front of the participant. After the food rating task, participants were calibrated using the standard nine-dot calibration procedure provided by the manufacturer.

In this experiment 46% of the participants had their rich side on the left during the first search task. On average, the maximum number of times any one item was seen was 14.32.

5.2. Results

5.2.1. Training

We first checked the accuracy during the first and second search tasks, as in Experiment 3. During the first search task, mean accuracy was 96.29% (se = 1.50%) and did not differ between the rich and sparse side in a two-sided *t*-test (mean accuracy difference = 0.69%, t = 1.23, 96% CI [−0.45%, 1.82%], $d = 0.21$). In contrast to accuracy, but in line with all of the prior studies, RT did significantly differ between the rich and sparse sides during the first search task (mean difference = 426 ms, t = 5.94, 95% CI [280 ms, 572 ms], $d = 1.003$) (Fig. 2E).

In line with (Jiang et al., 2014), we found that participants were significantly more likely to look at the rich side first during the search task (mean proportion of trials = 0.66, t = 4.37, 95% CI [0.59, 0.74]) (Fig. 2G). This confirms that the attentional biasing indeed affected participants' eye movements.

In the second search task, accuracy was 99.01% (se = 0.24%) and did not differ between sides (mean accuracy difference = 0.32%, t = 1.33, 95% CI [−0.17%, 0.82%], $d = 0.22$). As in Experiment 3, the terms "rich" and "sparse" always refer to the original rich and sparse sides unless otherwise specified. As expected, and in line with Experiment 3 (Section 4.2.1), the RT difference between the rich and sparse side was now negligible (mean difference = 34 ms, t = 0.50, 95% CI [−103 ms, 171 ms], $d = 0.09$). When we break the RT difference down to 50-trial blocks, we see that participants quickly unlearned the original training within the first 50 trials, as there was no significant difference in RT between sides (mean difference = 162 ms, t = 1.62, 95% CI [−366 ms, 41 ms], $d = -0.27$). By the final 50 trials, participants had learned the new probability structure and the RT difference reversed (participants were faster to respond to targets on the sparse side), although it was still not significantly different from zero (mean difference = 153 ms, t = 1.70, 95% CI [−30 ms, 338 ms], $d = 0.29$) (Fig. 2F).

In a similar fashion, first fixations showed no bias towards either side until the final block of 50 trials where they were biased towards the sparse side (mean proportion of trials in the final block = 0.59, 95% CI [0.51, 0.67]) (Fig. 2H). Thus, participants' eye-movements mirrored their RT differences in the search tasks.

5.2.2. Test – main effect

Looking at only the first 130 choice trials, we ran a simple mixed-effects logistic regression of fixating the rich side first on rating difference. Here we find no significant effect of rating difference on first fixations ($\beta = 0.020$, 95% CI [−0.064, 0.104]), which is in line with previous literature (Krajbich et al., 2010).

Importantly, we do find a significant bias to fixate the rich side first, as evidenced by a positive intercept ($\beta = 0.335$, 95% CI [0.023, 0.647]), indicating that the attentional bias did transfer to the choice task (Table S13).

We next investigated how this first-fixation bias translated into behavior by running the same mixed-effects logistic regression as that in Experiment 3 (Section 4.2.2): choosing the rich side on rating difference. Participants showed a significant bias to choose the item on the rich side (intercept $\beta = 0.087$, 95% CI [0.028, 0.146]) (Table S12).

5.2.3. Test – establishing the role of attention

While we have shown that our manipulation biases both first-fixation location and choice, it is not yet clear that there is a trial-level effect of first-fixation location on choice. To establish the link between first fixation and choice, we ran another mixed-effects logistic regression of choosing the rich side on rating difference and first-fixation location. Critically, the effect of first-fixation location on choice was strongly positive ($\beta = 0.354$, 95% CI [0.215, 0.493]), and the choice bias for trials with the first fixation to the sparse side was negative ($\beta = -0.114$, 95% CI [−0.220, −0.008]).

It is important to note at the outset that the following analyses are underpowered, since the sole aim of this experiment was simply to establish the eye-tracking effects. With only 35 participants, we should not expect to reliably demonstrate the individual-difference effects seen with greater sample sizes in the previous experiments. Nevertheless, for completeness, we report the results of those analyses here.

Focusing on the first 130 choice trials, we added the RT difference from the first search task into the aforementioned regressions. We first investigated whether those who learned the probabilities in the first search task, as measured by a larger RT difference, also demonstrated more of a first-fixation bias while controlling for the rating difference. Indeed, we found a strong positive relationship between RT difference and the first-fixation bias ($\beta = 0.819$, 95% CI [0.143, 1.495]). This indicates that those who better learned the attention manipulation were more likely to look at the rich side first during the choice task.

As before, the rating difference did not predict first fixations ($\beta = 0.020$, 95% CI [−0.064, 0.104]). The intercept also becomes non-significant ($\beta = -0.005$, 95% CI [−0.401, 0.391]), as expected after accounting for the degree of attentional learning (RT difference) (Table S13).

We looked at whether this pattern of results held for the choice behavior as well by running the mixed-effects logistic regression of choice on rating difference and RT difference.

The RT difference effect was in the predicted direction, though it did not reach significance ($\beta = 0.136$, 95% CI [−0.062, 0.334]) (Fig. 3D). Again, we expect and find no overall choice bias ($\beta = 0.036$, 95% CI [−0.064, 0.136]) after accounting for the degree of attentional learning (Table S12).

5.2.4. Test – post extinction

We next ran these same analyses on the second set of 130 choice trials. When predicting first fixations from rating difference, there is again no significant effect of rating difference ($\beta = 0.012$, 95% CI [−0.086, 0.110]), and participants no longer showed a significant tendency to fixate the rich side first ($\beta = 0.175$, 95% CI [−0.141, 0.491]). Similarly, choice behavior was also no longer significantly biased towards the rich side (intercept $\beta = 0.015$, 95% CI [−0.079, 0.109]) (Tables S15 and S16).

As with Experiment 3, additional regressions including RT difference from the two search tasks paint a complex picture and are described in detail in the supplements. Again, direct comparisons between the two choice tasks failed to reveal any significant differences (Tables S18–S20).

5.2.5. Dwell time effects

In accordance with our pre-registration, we also investigated whether there were biases in the total dwell time advantages to the rich side in either choice task. None of these effects approached significance, and we report them in the supplements (Tables S14, S17, & S20). Moreover, accounting for the dwell time advantage in the choice regressions did not reduce the choice bias, if anything it increased it (Table S12). These results confirm past findings on the effect of dwell time on choice but indicate that our attention manipulation operated through a different mechanism, namely an initial bias due to first-fixation location.

6. Pooled data analysis

A recent paper by Scheibehenne et al. (Scheibehenne, Jamil, & Wagenmakers, 2016) highlighted a method to study the consistency of results across studies. This type of analysis is useful for interpreting our data, given the fact that our effects were consistently in the same direction, but in some cases were not statistically significant. Here we present such an analysis, in which we used only the one choice task from Experiment 1, the second choice task from Experiment 2, and the first choice task from Experiments 3 and 4, since these were the tasks where we expected participants to choose more often from the rich side.

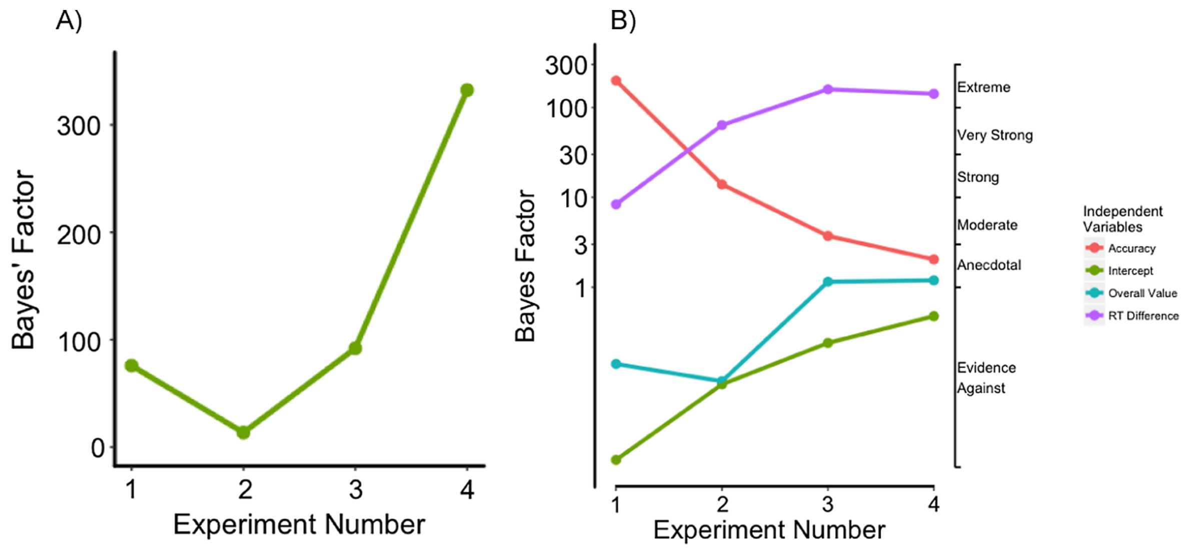

Fig. 4. Bayesian logistic regression results. Mixed-effects Bayesian logistic regression results from experiments 1, 2, 3 and 4 combined cumulatively. (A) Bayes Factor of the intercept being greater than 0 from the simple model p(choose rich side) ~ Rating Difference. (B) Bayes Factor of each coefficient of the full model p(choose rich side) ~ Rating Difference + Accuracy + Overall Value + RT Difference. Rating Difference is not shown here as the Bayes Factor was 9999 across all four studies.

All analyses were run using the BRMS package for R.

First we tested the simple model from each study, which is the mixed-effects logistic regression of choosing from the rich side as a function of the rating difference. Here we focused on the intercept and computed the Bayes factor testing whether participants had a bias to choose from the rich side vs. the alternative hypothesis of no bias. In order to avoid any biasing of the outcome, we used improper, uniform distributions over all real numbers as the priors on the intercept and rating difference coefficients.

Considering all four tasks, the Bayes factor for the intercept was 332. According to Scheibehenne et al. (2016), this indicates "extreme" evidence for a choice bias (see Fig. 4A for the evolution of the Bayes factor across studies; also Table S21). A more traditional frequentist *t*-test was also significant (p = 0.005) (Fig. 3F).

6.1. Establishing the role of attention

Next we tested a more complex version of the model, which included all the variables that were selected by our AIC comparisons in any of the experiments. This model thus included rating difference, accuracy, overall value, and RT difference. We again computed the Bayes factors for each variable being greater than zero and used uniform distributions over all real numbers as the priors on all the variables.

Considering all four tasks, the overall Bayes factors for the intercept, rating difference, accuracy, overall value, and RT difference were (respectively): 0.48 (anecdotal evidence against), 9999 (extreme), 2.04 (anecdotal), 1.194 (anecdotal), and 141.857 (extreme) (Fig. 4B). Thus we find extreme support for only rating difference and RT difference. A frequentist *t*-test on RT difference was also significant (p = 0.015) (Fig. 3E). Again, we expected the zero-to-negative intercept in this model after accounting for RT difference and accuracy.

This conclusion is supported when we compare AIC values for all the combinations of these variables in the meta-analysis (Table 1). From the pooled analysis we see that the best-fitting model includes only rating difference and RT difference. This confirms the overarching story that our search task had a significant effect on participants' food choices and that this effect was modulated by their attention bias (Fig. 4B). We see that for participants in the top 20% in terms of RT difference, their choice bias was 2.3%. To get a sense for the subjective magnitude of this effect, we went back to the original study by Krajbich et al. (2010), which used a very similar binary food-choice task. For a proper comparison with our current study, we focused solely on trials with the same range of rating differences (−1 to +1). In those trials, participants looked at the left item first on 75.4% of trials and chose the left item on 52.3% of trials. Thus, for our most influenced participants, it seems that with our simple 8-minute search task, we were able to erase or double (depending on the rich side) their average 'left-bias', a bias that has developed over their entire lives.

6.2. Decay over trials

A natural question to ask is whether the effects of our attention manipulation decay over time. That is, are participants' choices more spatially biased at the beginning of the choice block, compared to at the end? We examined this in each dataset by running mixed-effects logistic regressions predicting choice of the rich-side item as a function of rating difference and trial number. As before, we used only the one choice task from Experiment 1, the second choice task from Experiment 2, and the first choice task from Experiments 3 and 4, since these were the tasks where we expected participants to choose more often from the rich side. We find no evidence of a reduction in choosing the rich side over trials, in any dataset (Table 2).

7. Discussion

Here we have shown that manipulating spatial attention can influence which item a person will choose. In four separate experiments we manipulated attention using a spatially biased visual search task and then tested for a corresponding spatial bias in a subsequent food-choice task. Across the four experiments we found varying degrees of evidence for the hypothesized choice bias, which while small in size, was 332 times more likely to exist than to not, according to our Bayesian meta-analysis. We were also able to establish how well participants learned the attentional manipulation by measuring their spatial RT difference during the search task. This measure fully determined the effect of the search task on the choice behavior. It is worth noting that these effects are clearly driven by our manipulation and not reflective of any naturally occurring spatial biases, as the biases were randomly assigned and disappeared after the reversed search task (Experiments 3–4).

In addition to the RT effect, we also presented eye-tracking evidence, which mirrors the results of prior work using probability cueing, namely that it biases initial fixations (Jiang et al., 2014). Consistent with our current results, past research with the aDDM has demonstrated

Table 1
Meta-analysis results. Bold indicates significance at p ≤ 0.05. Italics indicate the best-fitting model.

Dependent variable	Intercept (bias)	Rating diff.	Overall value	Training accuracy	Training RT Diff.	AIC
Choose rich side	**0.034**	**0.401**				61,255
	(0.009, 0.059)	(0.370, 0.432)				
		0.399				61,327
		(0.368, 0.430)				
	0.033	**0.401**	0.001			61,253
	(−0.004, 0.070)	(0.370, 0.432)	(−0.032, 0.034)			
	−0.092	**0.401**		0.130		61,256
	(−0.376, 0.192)	(0.370, 0.432)		(−0.166, 0.426)		
	−0.002	**0.401**			**0.074**	61,252
	(−0.037, 0.033)	(0.370, 0.432)			(0.021, 0.127)	
	−0.108	**0.401**	0.001			61,256
	(−0.384, 0.168)	(0.370, 0.432)	(−0.032, 0.034)			
	−0.005	***0.401***	*0.002*		***0.074***	*61,249*
	(−0.049, 0.041)	*(0.370, 0.432)*	*(−0.031, 0.035)*		*(0.021, 0.127)*	
	−0.111	**0.041**		0.113	**0.073**	61,255
	(−0.385, 0.163)	(0.370, 0.432)		(−0.171, 0.397)	(0.022, 0.124)	
	−0.131	**0.401**	0.002	0.132	**0.074**	61,252
	(−0.407, 0.145)	(0.370, 0.432)	(−0.031, 0.035)	(−0.154, 0.418)	(0.023, 0.125)	

Table 2
Effects of trial number on the choice bias.

	Dependent Variable			
	P(Choose Rich Side)			
	Exp. 1	Exp. 2	Exp. 3	Exp. 4
Intercept	0.106*	0.022	0.070**	−0.009
	(0.058)	(0.029)	(0.033)	(0.062)
Rating Difference	0.418***	0.352***	0.447***	0.492***
	(0.038)	(0.025)	(0.028)	(0.040)
Trial Number	−0.005	−0.002	−0.005	0.013
	(0.008)	(0.004)	(0.005)	(0.009)
Observations	4940	19,110	15,470	4420
Log Likelihood	−3358.947	−13,065.730	−10,482.330	−2979.034
Alaike Inf. Crit.	6729.894	26,143.460	20,976.660	5970.068
Bayesian Inf. Crit.	6768.925	26,190.610	21,022.540	6008.431

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

an effect of the first fixation on choice. For example, participants who are more likely to look left first are more likely to choose items on the left. Interestingly, here first fixations did not influence choice via dwell time, perhaps suggesting a non-linearity in the decision process that favors early information. Such non-linearities are a feature of several prominent sequential sampling models, including the Ornstein-Uhlenbeck model (Ratcliff & Smith, 2004) and the Wang model (Wang, 2002), though notably not the standard DDM. It is worth noting that some prior research with the aDDM has indicated that the effect of the first fixation may be larger than predicted by the model (Krajbich et al., 2010, but see Krajbich & Rangel, 2011; Cavanagh et al., 2014).

Our results provide novel evidence for a causal effect of attention on choice. From a modelling standpoint, the aDDM merely captures a mathematical relationship between gaze and choice; it is agnostic about the direction of causality. Its key insight is that the value information being sampled over the course of the decision is not i.i.d., as assumed by most other sequential sampling models (though not decision field theory). Instead, value information is preferentially biased towards one alternative during certain time intervals, and these biases are tied to gaze. It could be that gaze merely reflects the shift in information sampling, or it could be that gaze causes the shift in sampling.

Proponents of the gaze-cascade effect have argued that both mechanisms are at play, with preference driving gaze (Shimojo et al., 2003). Proponents of the aDDM have instead argued that it is primarily gaze that drives preference, based in part on a lack of correlation between dwell times and independently measured stimulus values (Krajbich et al., 2010). Either way, we would expect that gaze manipulations would influence choice.

While a few papers have provided such evidence, ours overcomes some of their potential limitations and extends the scope of this link to temporally distinct settings. Prior work has manipulated gaze time (Armel et al., 2008; Lim et al., 2011; Shimojo et al., 2003), prompted a decision once a certain gaze criterion is fulfilled (Pärnamets et al., 2015; Tavares et al., 2017), made certain items more visually salient (Mormann et al., 2012; Towal et al., 2013) or systematically placed better items on one side of the screen (Colas & Lu, 2017). While it is reassuring that all of these manipulations lead to the predicted choice biases, there are some concerns with each of these manipulations. The primary concerns include interfering with the natural choice process, altering the stimuli, and manipulating value expectations.

Interfering with the natural choice process might be problematic, because while we control which item the subject is looking at, this does not mean that we control which item the subject is attending to. The subject may be forced to look at Coke, but still be focused on Pepsi. We see this possibility as very unlikely when subjects are free to look at Coke and Pepsi as they please. Related literatures have worried about the effects of interfering with cognitive processes, for example using Mouselab to reveal information with mouse clicks (Lohse & Johnson, 1996), or "think-aloud" paradigms (Leow & Morgan-Short, 2004). Thus, there is precedent to be concerned about experimenter manipulations of the choice process. Our study avoids this issue by placing no constraints on our participants during the choice tasks.

Altering the stimuli themselves may be problematic for the simple reason that it might facilitate identification (e.g. through perceptual fluency), explaining why, for example, people greatly prefer the salient item under very short exposure, but less so with longer exposure (Mormann et al., 2012). We know that people are generally uncertainty-averse, and so if faced with two items, one known and one unknown, people will generally prefer the known item. Our study avoids this issue by placing no time constraints on our participants, allowing them time to identify both alternatives.

Manipulating value expectations is problematic because adaptive decision makers should develop a response bias, based on their belief that this side of the screen is more likely to contain the better option. Our study avoids this issue by randomly assigning options to the rich and sparse sides during the choice task, and by holding constant the value of finding a target on each side during the search task.

An additional feature of our study is that it demonstrates that attentional biases developed in one setting can have impacts in other settings. For example, cultural differences in reading direction might lead to biases in whether people look left or right first, which in turn would influence how often they choose items on the left.

One potential concern with our study, as well as results from other attention-manipulation studies, is experimenter demand. It is possible that participants thought that they should choose items on the rich side of the display. We took steps to reduce this possibility by incentivizing the decisions, which is a standard approach for combatting demand effects in experimental economics. We also avoided interleaving the search and choice tasks, to minimize the likelihood that subjects would form a connection between the two. Finally, our analyses demonstrated that measures of attentional biasing (training RTs and initial fixations) predicted the size of subjects' choice biases, arguing against a simple response bias.

Our results are also consistent with the literature on perceptual fluency. That literature has argued that the ease with which information is perceived, influences preferences. Factors that facilitate perception, such as prior exposure, primes, or visual contrast, appear to affect preference judgments (Reber et al., 1998; Winkielman & Cacioppo, 2001; Zajonc, 1968). Perceptual fluency might be one of the mechanisms by which attention increases the rate of evidence accumulation and thus biases choices. The distractor devaluation effect is likely also closely related to our work, as there attentional inhibition of a distractor stimulus leads to reduced preferences for those stimuli (Fenske & Raymond, 2006).

In conclusion, our results support a causal mechanism from attention to choice. Therefore, inherent biases or exogenous manipulations of attention will, in turn, result in choice biases. A better understanding of attentional processes, biases, and salience are thus likely critical to the study of decision-making.

Author contributions

All authors developed the study concept and design. Data collection and analysis were performed by R. Gwinn. R. Gwinn drafted the manuscript with revisions from I. Krajbich and A. Leber. All authors approved the final version of the manuscript.

Supplementary material

Data repository
Experiments 1–3: https://osf.io/te2fz/
Experiment 4: https://osf.io/yn5g4/
Pre-Registrations
Experiment (2) https://osf.io/7mkn4/register/565fb3678c5e4a66b5582f67
Experiment (3) https://osf.io/y9m7s/register/565fb3678c5e4a66b5582f67
Experiment (4) https://osf.io/x8mvp/register/565fb3678c5e4a66b5582f67

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cognition.2018.10.012.

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