# Peripheral visual information halves attentional choice biases

Brenden Eum[1,3], Stephanie Dolbier[2,4], and Antonio Rangel[1,5]

[1]Department of Humanities and Social Sciences, California Institute of Technology, Pasadena, CA 91125
[2]Deparment of Psychology, University of California, Los Angeles, CA 90095
[3]beum@caltech.edu
[4]sydolbier@gmail.com
[5]arangel@caltech.edu

October 25, 2021

**Abstract**

A growing body of research has shown that simple choices (e.g., apple vs. orange) involve the construction and comparison of values at the time of decision. These processes are modulated by attention in a way that leaves decision makers susceptible to attentional biases so that, for example, the likelihood of choosing a product increases with the relative amount of overt visual attention that it attracts. Importantly, choice environments vary on the amount of peripheral information available. Sometimes we are presented with all of the available options at once (e.g., supermarket shelf), while others we are only shown one option at a time (e.g., many shopping websites). Here we study the role of peripheral visual information on the choice process and on attentional choice biases. We use an eye-tracking experiment where subjects make binary choices between food items that are displayed in marked screen "shelves" in two different conditions: (1) a simultaneous condition in which both items are displayed, and (2) a gaze contingent condition in which items are only displayed when subjects fixate within their shelves. We find that removing the nonfixated option slows down the choice process by about 32% and has little impact on the quality of average choices, but that it approximately doubles the size of the attentional biases. The results suggest that covert visual attention plays a key role in facilitating good decisions.

***Classification***— Psychological and Cognitive Sciences, Social Sciences
***Keywords***— decision making, attention, fixations, simple choice, neuroeconomics

**Significance Statement** We compare the choice processes and attentional biases at work in settings where all available options are presented (e.g., supermarket shelf) with settings where only one option is shown at a time (e.g., many shopping websites). We find that the same class of decision algorithms explains both types of choices, but that attentional biases double in size when only one option is shown at a time. This has practical and conceptual implications. In practice, it suggests that individuals might be substantially more influenceable by point-of-sale marketing in settings in which only one item is shown at a time, such as e-commerce, than in traditional retail settings. Conceptually, it shows that covert visual attention plays a critical role in facilitating good decisions.

**Author Contributions** A.R. designed research; S.D. collected data; B.E. analyzed data; and B.E. and A.R. wrote the paper.

**Funding** Financial support from the NOMIS Foundation is gratefully acknowledged.

**Competing Interests** The authors declare no competing interests.

# Introduction

Everyday we face two different types of choice situations. Sometimes we are presented with all of the available options at once, as when we face a supermarket shelf or a buffet table. In other cases, such as many shopping websites, we are presented with one option at a time, which changes sequentially at our own pace. In both cases our overt visual attention is deployed to one option at a time. But the two situations differ on the availability of peripheral visual information about the nonfixated options, which in principle could be used to guide the choice process.

A growing number of experiments have studied the role of visual attention in simple choice and have found that increases in the relative attention received by a desirable option are associated with an increase in the frequency with which it is chosen, all else being equal [1–13]. Although the exact mechanism behind the attentional bias remains unknown, foveation seems to facilitate the process of value computation and integration in a way that is consistent with overweighting fixated items relative to nonfixated ones. This is formalized in the Attentional Drift-Diffusion-Model (aDDM), which is able to provide a quantitative account of the relationship between fixations, choices, and reaction times [1–5]. The aDDM predicts that choices can be biased through exogenous manipulations of relative fixation time, consistent with the findings of multiple studies [14–21].

Our goal is to study the role of peripheral visual information on the choice process and on attentional choice biases. In particular, do we use the same choice algorithm when all options are presented simultaneously, as when we shop at the market, and when they are presented sequentially, as when we shop online? If not, does the absence of peripheral information change the fixation process and the magnitude of the attentional biases?

We study these questions using an eye-tracking experiment in which subjects make binary choices between foods that are displayed in marked screen "shelves" in two different conditions: (1) a simultaneous condition in which both items are displayed on the screen at the time of choice, and (2) a gaze contingent condition in which items are only displayed when subjects fixate within their shelves. Most previous studies have used choice tasks in which all options are displayed simultaneously, although a handful have used gaze-contingent presentation of stimuli [8, 22–24]. However, none have compared the two situations directly, which is necessary to understand the effect of peripheral visual information on the choice process.

Based on what is known about choice in the simultaneous case, and the seemingly minor change involved in removing the nonfixated options from peripheral vision, it is natural to hypothesize that similar algorithms are at work in both conditions, albeit with some differences. In particular, the aDDM suggests two non-mutually exclusive mechanisms through which removing the nonfixated options from the visual field might affect choices. First, it might increase the overweighting of fixated relative to nonfixated items, which would result in an increased attentional bias. Second, it might change the fixation process in a way that exacerbates the attentional biases, for example by increasing the asymmetry on fixation time across options. A natural competing hypothesis is that the choice process is dominated by information sampled from memory, in which case the removal of peripheral information should have minimal impact on choice.

Understanding the role of peripheral visual information in simple choice is important for several reasons. First, despite the robustness of the attentional biases identified in previous work, we do not know what are the channels through which covert and overt visual attention influence decisions, nor their relative contribution to choice. Second, although there is a growing consensus that simple choices involve the integration of noisy value signals, their nature is not well understood. Some have proposed that value signals involve the sampling and valuation of stimulus attributes from their visual representations [25, 26], which could be carried out through peripheral vision. In contrast, others have proposed that the value samples originate in episodic memory [27, 28], in which case peripheral vision might play a lesser role. Third, the transition to e-commerce has increased the frequency with which our decisions are made in sequential presentation settings. We need to understand the impact that this has on the choice algorithms and their associated biases in order to design interfaces and nudges that enhance choice quality [29, 30].

To preview the results, we find that removing the nonfixated options has little impact on the average quality of choices. However, we also find that it approximately doubles the magnitude of attentional choice biases, which make decision makers more susceptible to marketing interventions (e.g., packaging) that affect attention independently of the value of products. We also find that the removal of the nonfixated options slows down the fixation and decision process considerably, but that the impact on attentional biases is driven mostly by an increase in the tendency to overweight the value of fixated options.

# Results

We investigated the role of peripheral information about nonfixated stimuli using the task depicted in Fig. 1. Subjects made 360-400 binary food choices, and at the end were given the snack that they chose on a randomly selected trial. Prior to the choice task, subjects provided liking ratings for 60 different snacks, which we use as independent measures of each subject's utility for consuming them. Subjects made decisions in two conditions: (1) a visible condition in which both items were displayed on the screen at the time of choice, and (2) a hidden condition in which items were displayed only when subjects fixated within the location associated with the stimulus. To minimize differences across the two conditions, both options were surrounded by a white square indicating their location. Subjects indicated their choice, when ready, through a keyboard press. See Methods for details.

In order to be able to explore the data in detail, while avoiding the type of statistical problems that have raised questions about the validity of some published research [31–33], we collected two separate data sets with 25 subjects each. We used the first one to carry out exploratory analyses until we understood the data generating process in sufficient detail. Based on this, we pinned down a set of analyses and tests that were carried out in a second confirmatory data set of equal size. Thus, the confirmatory data set serves as a replication of our findings, and provides unbiased statistics for hypothesis testing. Given the similarity of the estimates and findings in both samples, and in the spirit of meta-analysis, we also provide results on the pooled sample and describe summary statistics in terms of the pooled estimates.

**Basic Psychometrics.** The top row of Fig. 2 depicts the psychometric choice curve, separately for each experimental condition and dataset. See Table S1 for the associated regression estimates and test statistics. We find a small but significant increase in the responsivity of choices to value differences in the hidden condition. The middle row of Fig. 2 depicts reaction times (RTs) as a function of choice difficulty. We find that RT increases with choice difficulty, that average RTs are about 40% (517 ms) slower in the hidden condition, and that this slowdown does not vary significantly with choice difficulty. The bottom row of Fig. 2 depicts the number of fixations as a function of choice difficulty. We find that the number of fixations increases with choice difficulty, and are approximately similar in both conditions, except for a small flattening in the slope of the fixation curve in the hidden condition.

Together, these results show that removing the nonfixated items slows down the choice process, but has only a minuscule effect on the quality of average choices (probability best chosen visible = $0.849 \pm 0.002$, probability best chosen hidden = $0.864 \pm 0.002$, p = 1.88e-06).

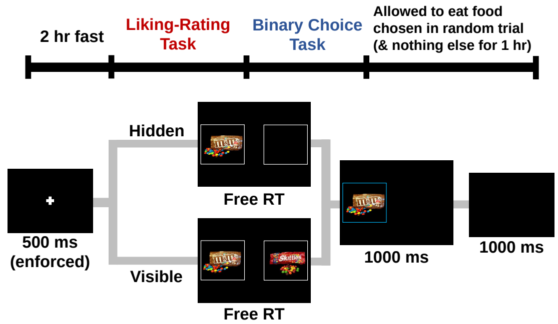



**Figure 1: Task.** Subjects had to fixate on a center fixation cross for 500 ms for the trial to start. In the visible condition subjects were presented with two snack food items simultaneously, each located within a white box on the left and right sides of the screen. In the hidden condition subjects had to fixate within the white boxes in order to reveal the snack food item inside. Subjects indicated their response at their own pace with a keyboard press. Once a choice was made, a blue box highlighted the selection for 1 s, followed by a 1 s inter-trial interval.

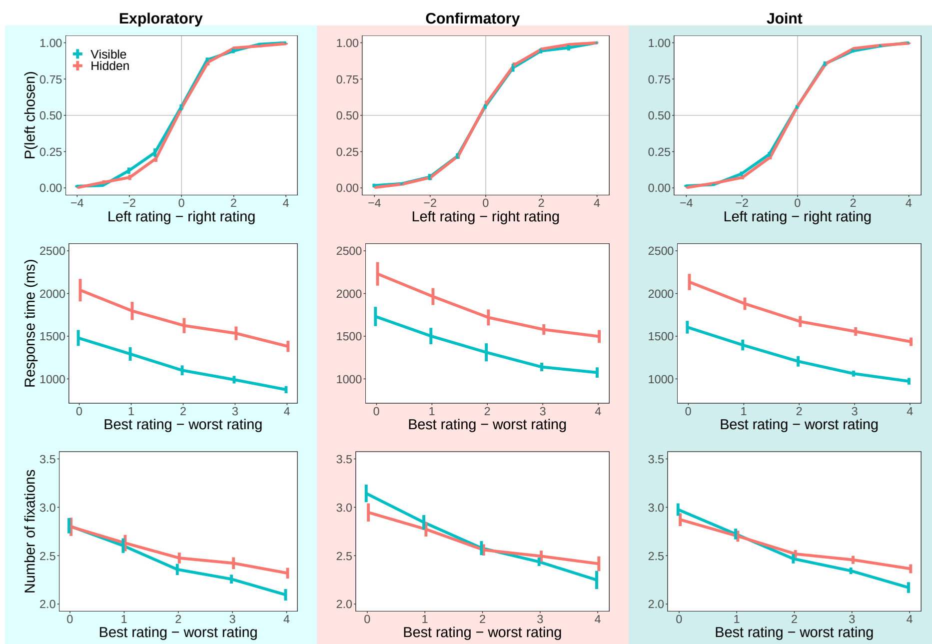



**Figure 2: Basic psychometrics.** *Top:* Probability of left item chosen as a function of its relative value. *Middle:* Response time as a function of trial difficulty, as measured by the rating difference between the best and worse items. *Bottom:* Number of fixations as a function of trial difficulty. Columns indicate which dataset generated the figures. Bars denote SEs.

**Fixation process.** Fig. 3 and Table S2 explore the fixation process in more detail. The goal here is to understand the impact that removing nonfixated items has on the fixation process, which is essential to understand how it affects attentional biases.

The top row depicts the probability that the first fixation is to the best item, as a function of choice difficulty. The first fixation location is at chance in both conditions. Fig. S3 and Table S4 show that there is also no difference between conditions on the latency to the start of the first fixation.

The second row depicts the mean duration of first, middle, and last fixations, separately for the two conditions. We find that the three types of fixations are longer in the hidden condition by about 40% on average (first=160ms; middle=145ms; last=191ms). Note that this is consistent with the RT results above: an average trial has 3 fixations, and each fixation is on average 165 ms longer in the hidden condition, which implies that decisions should take 495 ms longer, just shy of the observed RT difference.

The third row depicts middle fixation durations as a function of choice difficulty. We find that middle fixation durations increase with choice difficulty, and are a bit more responsive to choice difficulty in the hidden condition. Fig. S2 and Table S3 show that this difference is driven by the value of the fixated item: in the hidden condition middle fixation durations increase with the value of the fixated item, whereas the opposite occurs in the visible condition. Interestingly, Fig. S2 also shows that middle fixation durations decrease with the value of the nonfixated item even in the hidden condition.

The fourth row depicts the first fixation duration as a function of choice difficulty. We find that duration is independent of value in both conditions, and about 44% (155 ms) longer in the hidden condition. See Fig. S2 and Table S3 for further results.

The bottom row shows the relationship between relative value and relative fixation time. In both conditions, the relationship exhibits an S-shape. Both items are fixated the same amount when they have equal value, but otherwise the better item is fixated longer, with the asymmetry on fixation time increasing in the value advantage. In addition, the effect is stronger in the hidden condition, and as a result the distribution of net fixation times is more asymmetric in favor of the better item in this condition. Note that, since the fixated item is overweighted in the aDDM, this asymmetry in relative fixation time facilitates choosing the better option.

**Choice biases.** Fig. 4 and Table S5 depict the attentional bias in both conditions. The goal here is to provide a model-free test of the extent to which removing nonfixated items affects attentional biases.

The top row depicts the probability of choosing the left item as a function of its relative rating and the location of the last fixation. In the absence of an attentional bias, the location of the last fixation should not matter and the choice curves should lie in top of each other. In contrast, and consistent with previous studies [1–5, 12, 15], we find a substantial attentional bias in the visible condition: on average, when the left and right items are equally valued, the left item is 2.5 times more likely to be chosen when the last fixation is to left than when it is to right. The bias is substantially larger in the hidden condition, where the left item is 5 times more likely to be chosen when the last fixation is to the left than when it is to the right.

The middle row depicts the relationship between net fixation time and the corrected probability of choice. The choice measure is corrected by subtracting from each choice observation (coded as 1 if left chosen, and 0 otherwise) the proportion with which left is chosen at each relative value. As a result, in the absence of an attentional bias, the corrected probability of choice should be 0, independent of net fixation time. In contrast, we find that shifting net fixation time towards the left item by 1 second increases its choice probability by 23% in both conditions.

The bottom row depicts the relationship between the first fixation duration and the corrected choice probability of the first seen item, using the same correction described above. In the absence of an attentional bias, the corrected probability should be 0 for all fixation durations. We find that increasing the first fixation duration by 1 second increases the choice probability by about 19% in the visible condition, but that first fixation duration has no significant effect on choice probability in the hidden condition.

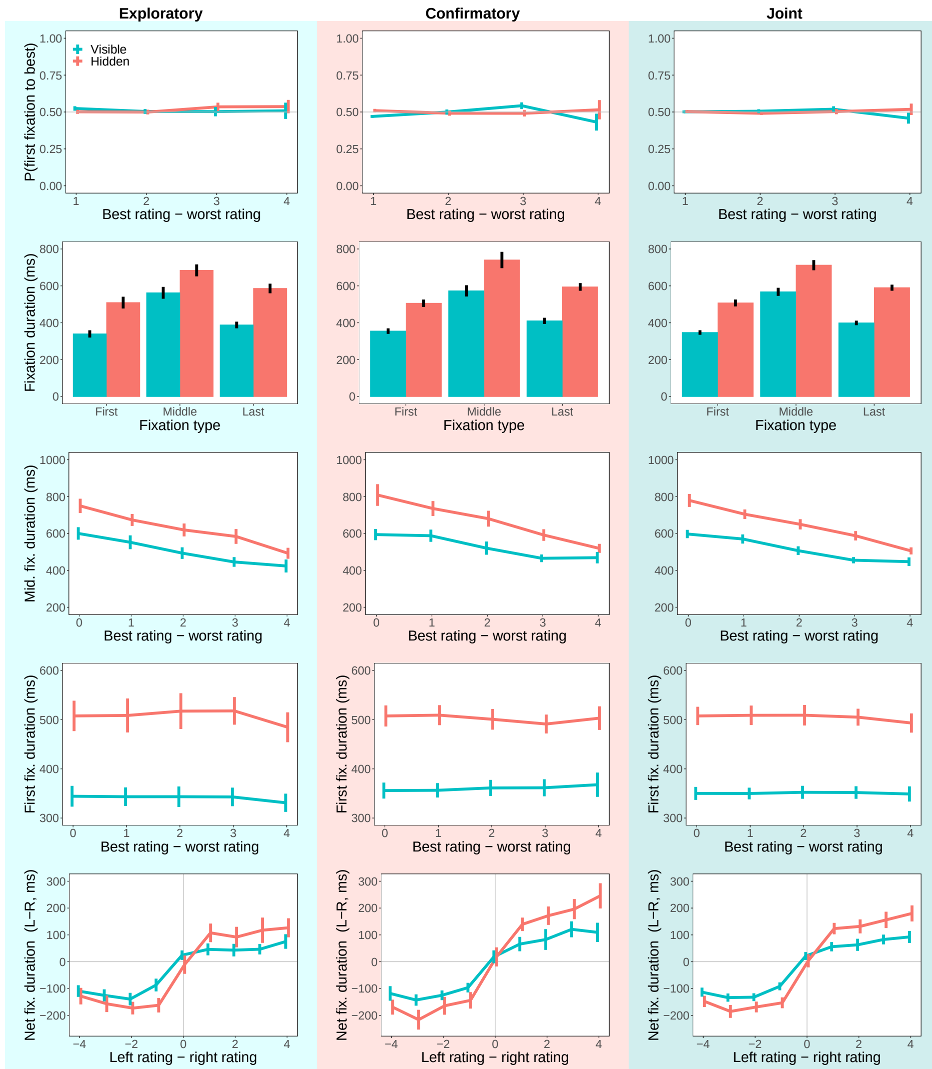



**Figure 3: Fixation properties.** *Row 1:* Probability that the first fixation is to the best item as a function of choice difficulty. *Row 2:* Fixation durations by fixation type. *Row 3:* Middle fixation duration as a function of choice difficulty. *Row 4:* First fixation duration as a function of choice difficulty. *Row 5:* Net fixation duration to the left item as a function of its relative value. Columns indicate which dataset generated the figures. Bars denote SEs.

**aDDM.** Given that the aDDM has been shown to provide good quantitative accounts of the relationship between fixations, choices, and RTs, we fit this model to our data, separately for the visible and hidden conditions. The goal is to investigate the impact of removing the nonfixated items on the parameters of the aDDM and the attentional biases that they predict.

As illustrated in Fig. 5A, the aDDM is a version of the Drift-Diffusion-Model of binary choice [34–36] in which value sampling is affected by fixation location. Subjects integrate noisy values signals into an evolving relative decision value (RDV). The RDV starts every trial at an initial location $b$, which may include some bias towards one of the options if $b \neq 0$. A choice is made the first time RDV crosses one of two pre-specified barriers, which are fixed at 1 for the left item, and -1 for the right item. The identity of the barrier crossed specifies which option is chosen. Critically,

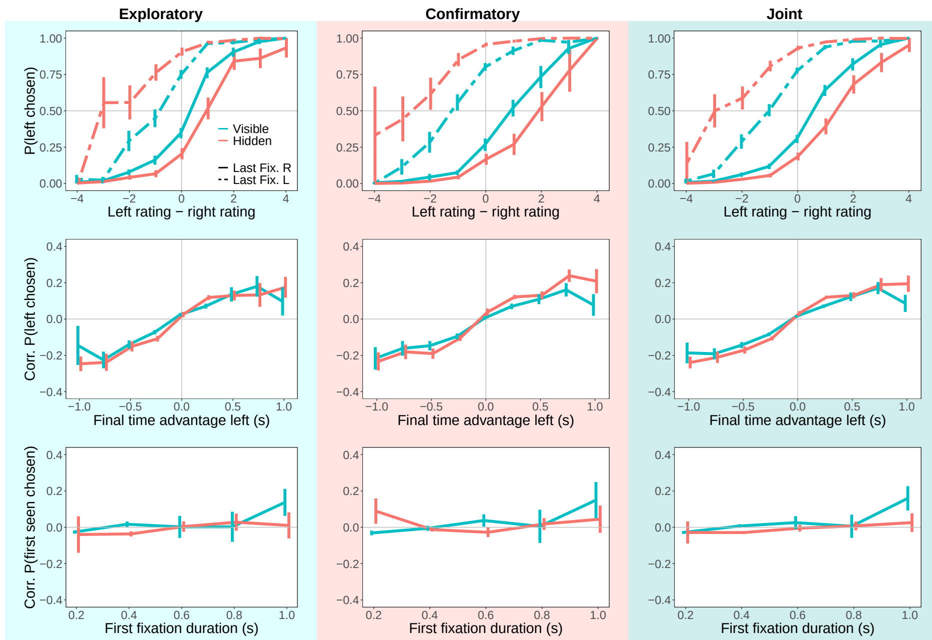



**Figure 4: Choice biases.** *Top:* Probability of choosing the left item as a function of its relative value, conditional on last fixation location. *Middle:* Corrected probability of choosing the left item as a function of the net fixation time to the left item. Corrected probability is computed by subtracting from each choice observation (coded as 1 if left chosen, and 0 otherwise) the proportion with which left is chosen at each relative value. *Bottom:* Corrected probability that the first seen item is chosen as a function of first fixation duration. Columns indicate which dataset generated the figures. Bars denote SEs.

the RDV evolves as the following diffusion process:

$$RDV_t = RDV_{t-1} + \mu_t + e_t \tag{1}$$

where $e_t$ is i.i.d. white Gaussian noise with variance $\sigma^2$, and the slope of the process depends on the fixation location. In particular, when the left item is fixated, the slope of integration is $\mu_t \sim N(d(v_L - \theta v_R), \varepsilon)$, and when the right item is fixated it is $\mu_t \sim N(d(\theta v_L - v_R), \varepsilon)$, where $d$ is a parameter controlling the speed of integration, $\theta$ is a parameter controlling the attentional bias, and $\varepsilon$ is a parameter controlling the inter-trial variation in the speed of integration. When $\theta = 1$, the fixations do not affect choices, there are no attentional biases, and the process reduces to a standard DDM. In contrast, when $\theta < 1$, the value of the fixated item is overweighted relative to the nonfixated value, which results in an attentional bias that increases as $\theta$ gets smaller.

The aDDM has five free parameters ($d$, $\sigma$, $\theta$, $b$, and $\varepsilon$) that we fit using a hierarchical Bayesian model. We fit the model using only odd trials, so that we can make out-of-sample predictions using even trials. Importantly, the aDDM assumes that the fixation process is orthogonal to the state of the RDV in any given trial. Thus, in fitting and simulating the model, we sample fixations from the observed fixation distributions, conditional on being a first or middle fixation. See Methods for details.

Table 1 summarizes the MAP group parameter estimates. We find that $\theta_{hidden} = 0.24$ and $\theta_{visible} = 0.5$ ($\theta_{visible} - \theta_{hidden}$ 95% $CI = [0.18, 0.48]$) which means that the attentional bias parameter in the hidden condition worsens by a factor of two, consistent with the results de-

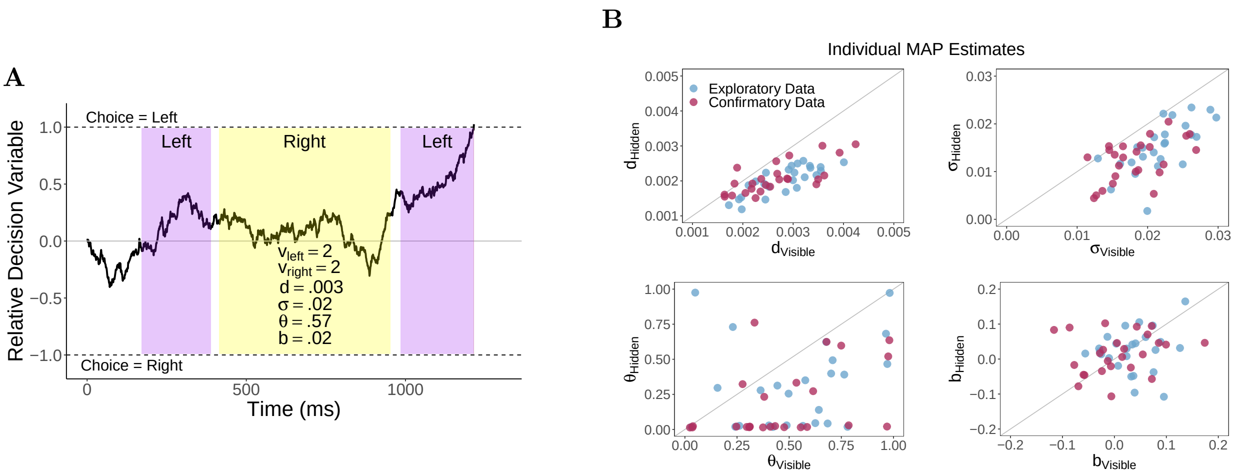



**Figure 5: aDDM.** *A.* Illustration of how the aDDM makes decisions in a sample trial. Colored vertical bands denote fixation location. *B.* Individual MAP parameter estimates in the visible and hidden conditions, for both the exploratory and confirmatory datasets.

scribed above. We also find differences in the estimated parameters for the slope ($d_{hidden} = 0.002$ vs. $d_{visible} = 0.003$, $d_{visible} - d_{hidden}$ $95\%\ CI = [0.0005, 0.0009]$) and noise ($\sigma_{hidden} = 0.014$ vs. $\sigma_{visible} = 0.02$, $\sigma_{visible} - \sigma_{hidden}$ $95\%\ CI = [0.004, 0.008]$)). The hierarchical model also provides individual parameter estimates for each subject, which are shown in Fig. 5B. Note that, except for the bias, the parameters in the visible condition are larger for most subjects. See Figs. S4 and S5 for a comparison of the out-of-sample predictions of the fitted model and the data in the even trials.

| | **Exploratory** | | **Confirmatory** | | **Joint** | |
|---|---|---|---|---|---|---|
| Parameter | H | V | H | V | H | V |
| $d$ | 0.002 | 0.003 | 0.002 | 0.003 | 0.002 | 0.003 |
| | (1e-04) | (1e-04) | (1e-04) | (1e-04) | (1e-04) | (1e-04) |
| $\sigma$ | 0.015 | 0.022 | 0.012 | 0.018 | 0.014 | 0.02 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\theta$ | 0.31 | 0.53 | 0.18 | 0.47 | 0.24 | 0.5 |
| | (0.06) | (0.05) | (0.05) | (0.06) | (0.04) | (0.04) |
| $b$ | 0.02 | 0.04 | 0.01 | 0.01 | 0.02 | 0.02 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| $\varepsilon$ | 2e-04 | 3e-04 | 3e-04 | 4e-04 | 3e-04 | 3e-04 |
| | (3e-08) | (1e-07) | (7e-06) | (2e-05) | (7e-07) | (8e-06) |

Mean and SE across subject-level MAP estimates.

**Table 1:** MAP aDDM parameter estimates

**Mechanisms of Choice Bias.** Our results show that attentional biases are approximately twice as large in the hidden condition, and that this is accompanied by a change in fixation durations, the key attentional bias parameter $\theta$ in the aDDM, and changes in other aDDM parameters. In this section we simulate data out-of-sample to explore the role of each of these changes.

The simulations are shown in Fig. 6. We start the analysis by comparing the observed and simulated attentional bias in the visible condition. To do this, we simulate 10 datasets for every subject in the out-of-sample even trials, using the empirical fixation patterns from the even trials and the aDDM parameters fitted in the odd trials of the visible condition (see Methods for details). As shown in the top panel, we find a good quantitative match between the observed and simulated data.

We then repeat the exercise changing only either the fixation process, or the value of the key attentional bias parameter $\theta$ in the aDDM. Panel B depicts data simulated using the parameters fitted in the visible condition but using the fixation process from the hidden condition. It shows that that this change, by itself, has a negligible impact on the attentional bias. In contrast, panel C depicts data simulated using the fixations from the visible condition, but using the values of $\theta$ fitted in the hidden trials. The panel shows that this change by itself generates a good qualitative account of the increased attentional bias in hidden trials.

Panels D and E show that once the change in the $\theta$ parameter is taken into account, including the change in observed fixations patters and the change in other aDDM parameters to the values fitted in the hidden conditions have a minimal effect on the predicted attentional biases. As a result, the simulations show that the impact on attentional biases is driven mostly by an increase in the tendency to overweight the value of fixated options.

# Discussion

Our experiment was designed to study the impact of peripheral visual information on the decision algorithm and its performance. Removing the nonfixated option has little impact on the quality of average choices, although it slows down the choice process by about 40% (or 517 ms). More importantly, we find that attentional choice biases are approximately twice as large when the nonfixated option is not shown.

The conclusion about the relative magnitude of the attentional biases in the two conditions is based on two different sets of analyses. A model free way of measuring the size of the attentional bias, that does not depend on the assumption that the aDDM is a good description of the data generating process [37], is to ask what is the probability of choosing the last fixated item when decisions have equal value (Fig. 4A). In the absence of an attentional bias, both items should be chosen with equal probability. In contrast, the last seen item is chosen on average 23% more than chance when all items are shown simultaneously and 37% more than chance when nonfixated items are hidden. Another way of measuring the attentional bias is based on the aDDM. In this model, the value of nonfixated options at any given time is downweighted by a parameter $\theta$. When $\theta = 1$, there is no attentional bias. When $\theta < 1$, there is an attentional bias in favor of the fixated item, which is stronger for lower values of $\theta$. Our mean estimates are $\theta = 0.5$ when all items are shown and $\theta = 0.24$ when nonfixated options are hidden. In both cases, the results show that removing peripheral visual information doubles the size of the attentional biases.

We find that middle fixations slow down by about 25% and first fixations slow down about 46% in the hidden condition, independently of the stimuli's value. There are two natural hypotheses for the mechanisms behind this change. One hypothesis, based on bottom-up control of the fixation process, is that the removal of peripheral stimuli changes the priority map that controls fixation

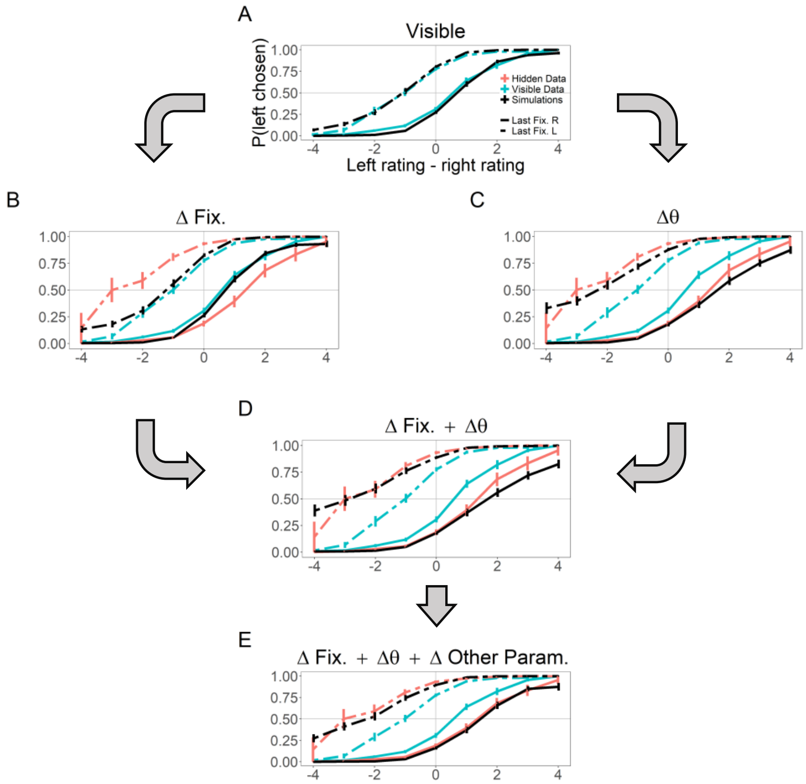



**Figure 6: Mechanisms of choice bias.** Comparison of the probability of choosing the left item, as a function of its relative value and last fixation location, in observed (blue, red) and simulated (black) data. Panels differ on the assumptions used to simulate the data. *A:* Simulated data for out-of-sample even trials using the empirical fixation patterns and MAP parameters fitted in the visible condition. The figure shows a good qualitative match in that condition. *B:* Same as panel A, except that the simulations used the empirical fixation patterns from the hidden condition. The figure shows that the simulated data still provides a good qualitative match to the visible condition. *C:* Same as panel A, except that the simulations used the $\theta$ MAP parameter fitted out-of-sample in the hidden condition. The simulated data now provides a good qualitative match to the hidden condition. *D:* Same as panel A, except that both the empirical fixation patterns and the $\theta$ MAP parameter are from the hidden condition. *E:* Same as panel A, except that now all the parameters used are those fitted in the hidden condition. 10 simulated observations per trial, per subject.

durations and locations [13,38–40]. This is consistent with findings from the visual search literature, which have found that a decrease in the saliency of peripheral stimuli, of which removal is an extreme case, increases fixation durations [41], as well as with the finding that fixation durations increase in patients with hemispatial neglect [42–44]. An alternative hypothesis, based on top-down control of the fixation process, is that fixations slow down to accommodate the increased difficulty of generating value samples for the nonfixated stimuli in the absence of peripheral visual information.

Beyond showing that attentional choice biases increase substantially when only one item is shown at a time, our findings also provide some novel clues about the mechanisms at work in simple choice.

First, we find that in the absence of peripheral stimuli the attentional bias parameter ($\theta$) is greater than zero, which means that the values of nonfixated items are still being processed, even if they are underweighted. This suggests that foveation facilitates the extraction of value samples, but that it is not necessary, at least after the second fixation when the identity of both stimuli becomes known. This also implies that covert attention is paid to the nonfixated item, at least after the second fixation. In fact, one interpretation of our results is that removing the nonfixated item reduces the amount of covert attention that it receives (see [45] for an outstanding review of the role of covert visual attention).

Second, there is an open debate about the mechanisms that generate the noisy value samples that are integrated during the choice process. One proposal is that value signals involve the sampling and valuation of stimulus attributes based on their visual representations [25, 26]. A competing proposal is that they involve episodic memories [27, 28]. Although our results cannot pin down the relative importance of these two non-mutually exclusive mechanisms, they provide some evidence against the pure memory hypothesis. After all, if value samples are retrieved from memory, it is hard to understand why covert access to stimulus images should affect the sampling process once the identity of both stimuli is known (after the second fixation).

Third, Bayesian models of information sampling in simple choice have proposed that fixations matter because they control which value samples are obtained, and that samples matter because they shift the value estimates from a common initial prior to posteriors that are closer to the true value of each stimulus. As a result, the value estimates of better-than-average items tend to increase with additional fixation time, and the opposite is true for worse-than-average items [46–49]. This Bayesian perspective could account for the increased attentional bias when nonfixated items are hidden, as long as value samples are taken in parallel from both choice options, but the rate of sampling is slower for the nonfixated items, and even lower if they are not present in peripheral vision. Note that, in contrast, existing Bayesian models have assumed that samples are obtained only from the fixated item.

Finally, our results also have implications for the growing field of choice architecture, which seeks to understand how seemingly minor changes in the choice environment affect decisions, and how to apply this information to help individuals make better decisions [50, 51]. We find substantially larger attentional biases in settings where only one option is shown at a time – as is done in many shopping websites – than in settings where all options are presented simultaneously – such as supermarket shelves. This suggests that individuals might be more susceptible to marketing influences that attract attention (e.g., salient packaging or point-of-sale ads) in the growing domain of e-commerce than in traditional retail settings. Although our experiments only measure the effect of removing peripheral stimuli, similar issues could arise in contexts where choice options are described sequentially using other sensory modalities (e.g., when a waiter describes the menu specials). Extrapolating from our results, we also hypothesize that similar increases in attentional biases could be induced simply by increasing the spatial separation between stimuli, so that it becomes difficult to process nonfixated options using peripheral vision. Consistent with this hypothesis, others have found that subjects with a narrower spatial attention tend to exhibit larger attentional choice biases than those with broader spatial attention [4].

# Methods

**Subjects.** 50 members of the Caltech and Pasadena communities completed the study (mean age = 30.8, 34 female). We pre-screened subjects for a self-reported liking for snack foods (e.g. candy and potato chips) and against requiring glasses for vision correction that might interfere with eye-tracking. Subjects were paid a $35 participation fee. The experiment was approved by Caltech's IRB.

In order to obtain high quality data, we implemented a subject filter at the data collection stage. Immediately after data collection we deleted subjects who failed any of the following criteria: (1) correlation between the two liking ratings of at least 70%, (2) mean RT in choice trials between 0.7 and 6 s, (3) probability of choosing the best item significantly different from chance (based on a binomial test), and (4) at most 10% missing fixation data. Data collection continued until 50 subjects passed the data quality criteria. The first 25 subjects were allocated to the exploratory sample, the other 25 to the confirmatory sample.

**Task.** Subjects were asked to refrain from eating for 2 h before the start of the experiment, and to refrain from eating any foods afterwards during a 1 h waiting period, except for the snack that they chose in a randomly selected trial, which was given to them at the end of the experiment.

They participated in two tasks. First, they were asked to provide liking ratings for 60 snack foods available at local stores ("How much would you LIKE to eat this food?", 1 = "don't like" to 5 = "like a lot", 0.25 intervals). Each item was rated twice, in random order, using a slider bar controlled by the arrow keys, and initialized to a random location to reduce anchoring effects. We use the average of the two ratings as a measure of each item's value.

Second, subjects made choices between two food items, shown on the left and right sides of the screen, in two separate conditions: (1) a visible condition where both items were shown simultaneously, and (2) a hidden condition where items were shown only when subjects fixated within their region of interest (ROI). The ROIs were indicated in both treatments with a white box (Fig. 1). Trials started with an enforced 500 ms central fixation. Subjects indicated their choices with the left and right arrow keys, and responded at their own pace. The selected option was highlighted for 1 s and trials were separated by a 1 s blank screen. Subjects made 360 choices in the exploratory sample and 400 in the confirmatory sample, half on each experimental condition. The task was divided into 4 equal sized blocks, 2 with the hidden condition and 2 with the visible condition, in random order.

The choice pairs in the exploratory data set were randomly selected from all 60 food items. In the confirmatory sample, they were constructed as follows. We used the ratings to prune the stimulus set down to the 40 food items that resulted in the most uniform distribution of ratings, in order to maximize the spread of rating differences across choice pairs. Stimuli for each trial were then randomly selected, subject to the constraint that they be used 4 times per block in the exploratory data set, and 5 times per block in the confirmatory data set. All 60 foods were shown once every 30 trials in the exploratory data set, and all 40 foods were shown once every 20 trials in the confirmatory data set.

**Eye-tracking.** Subjects' fixation patterns were recorded using an EyeLink 100 desk eye-tracker at 500 Hz. Subjects sat approximately 60 cm from a 1920×1080 pixel monitor. Food image sizes were 403×302 pixels. Fixations within the ROI for the left food were classified as "left", those within the right food's ROI were classified as "right", and those outside the two ROIs were classified as "blank". If a sequence of blank fixations was recorded between two fixations of the same type (e.g. left-blank-blank-left), they were re-coded as a fixation of the same type (e.g., left-left-left-left), since blank fixations of this type are typically due to eye-tracking noise and they tend to be quite short. Blank fixations recorded between two fixations of different type (e.g. left-blank-right) were coded as a saccade period between fixations. Trials in which any eye-tracking information is missing are dropped from further analysis (mean of 6 and 4 trials per subject in the exploratory and confirmatory samples, respectively).

**aDDM fitting.** We fit the aDDM using a hierarchical Bayesian model, separately for the visible and hidden conditions, using the methods and associated toolbox developed by Lombardi and Hare [52]. We estimate the model separately for the exploratory, confirmatory, and pooled samples. In every case, the model is fit using only the odd trials, as the even trials are reserved for out-of-sample predictions. As described in Fig. S1, the model has the following free parameters, both at the group and individual levels: the evidence accumulation drift rate ($d$), the standard deviation of the Gaussian noise for the drift process ($\sigma$), the attentional bias parameter ($\theta$), the initial bias of the drift process ($b$), and an error term that adds Gaussian noise to the slope of the drift process independently on each trial ($\varepsilon$). This error term is required in order to use the hierarchical Bayesian estimation toolbox to estimate the parameters of the aDDM [52]. Posterior distributions were estimated using Markov Chain Monte Carlo methods with 3 chains for a total of 150,000 burn-in samples and 30,000 samples from each of the posteriors.

**Out-of-sample simulations.** Even-numbered trials were set aside as out-of-sample data, in order to compare them to the predictions of aDDM model fitted on the odd trials. We simulate 10 data sets for each subject and condition, using the same rating pairs encountered in the experiment. For each simulated data set we sample a set of parameters from the joint posterior distribution for that subject and condition. Then we simulate each trial as follows. We sample all fixation duration statistics from their observed empirical distributions in the even trials, conditional on the hidden or visible condition. For example, when simulating a hidden condition trial, the RDV signal for the trial is initialized at the bias parameter and evolves based only on the noise up to the duration of the sampled latency to first fixation. Afterwards, a maximum first fixation duration is sampled from the distribution of first fixations in the hidden condition, and the RDV evolves according to the drift rate, noise, and attentional bias parameters depending on the fixation location, as described in the Results section. If a barrier is crossed before the maximum fixation duration is reached, the process is terminated and the choice and RT recorded. Otherwise, a new saccadic duration and maximum fixation duration are sampled from the distributions of saccades and middle fixations in the hidden condition, respectively. The process is repeated until a choice is made. Note that this assumes that the value of the nonfixated item is known during the first fixation, which is unrealistic and interferes with the quality of our fits.

**Hierarchical regressions.** All the logistic and linear regressions reported in the paper are based on standard hierarchical models with random coefficients for all parameters. The regressions were implemented using the brms R-package [53,54] and used the default weakly informative priors, occasionally scaled depending on the units of the independent variable. Posterior distributions were estimated using 3 chains for a total of 9,000 burn-in samples and 9,000 samples from each of the posteriors. See the companion data and code package for details.

**Data and code.** All data and code are available for download at the Rangel Neuroeconomics Lab website (`www.rnl.caltech.edu`).

# References


[1] I Krajbich, C Armel, A Rangel, Visual fixations and the computation and comparison of value in simple choice. *Nat. Neurosci.* **13**, 1292–1298 (2010).

[2] I Krajbich, A Rangel, Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proc. National Acad. Sci. U.S.A.* **108**, 13852–13857 (2011).

[3] I Krajbich, D Lu, C Camerer, A Rangel, The attentional drift-diffusion model extends to simple purchasing decisions. *Front. Psychol.* **3**, 193 (2012).

[4] SM Smith, I Krajbich, Attention and choice across domains. *J. Exp. Psychol. Gen.* **147**, 1810–1826 (2018).

[5] SM Smith, I Krajbich, Gaze amplifies value in decision making. *Psychol. Sci.* **30**, 116–128 (2019).

[6] JF Cavanagh, TV Wiecki, A Kochar, MJ Frank, Eye tracking and pupillometry are indicators of dissociable latent decision processes. *J. Exp. Psychol. Gen.* **143**, 1476–1488 (2014).

[7] SE Cavanagh, WM Malalasekera, B Miranda, LT Hunt, SW Kennerley, Visual fixation patterns during economic choice reflect covert valuation processes that emerge with learning. *Proc. National Acad. Sci. U.S.A.* **116**, 22795–22801 (2019).

[8] P Sepulveda, et al., Visual attention modulates the integration of goal-relevant evidence and not value. *eLife* **9**, e60705 (2020).

[9] AW Thomas, F Molter, I Krajbich, Uncovering the computational mechanisms underlying many-alternative choice. *eLife* **10**, 1–27 (2021).

[10] S Gluth, MS Spektor, J Rieskamp, Value-based attentional capture affects multi-alternative decision making. *eLife* **7**, e39659 (2018).

[11] S Gluth, N Kern, M Kortmann, CL Vitali, Value-based attention but not divisive normalization influences decisions with multiple alternatives. *Nat. Hum. Behav.* **4**, 634–645 (2020).

[12] G Fisher, An attentional drift diffusion model over binary-attribute choice. *Cognition* **168**, 34–45 (2017).

[13] RB Towal, M Mormann, C Koch, Simultaneous modeling of visual saliency and value computation improves predictions of economic choice. *Proc. National Acad. Sci. U.S.A.* **110**, e1304429110 (2013).

[14] KC Armel, A Beaumel, A Rangel, Biasing simple choices by manipulating relative visual attention. *Judgm. Decis. Mak.* **3**, 396–403 (2008).

[15] G Tavares, P Perona, A Rangel, The attentional drift diffusion model of simple perceptual decision-making. *Front. Neurosci.* **11**, 1–36 (2017).

[16] T Hare, J Malmaud, A Rangel, Focusing attention on the health aspects of foods changes value signals in vmpfc and improves dietary choice. *J. Neurosci.* **31**, 11077–11087 (2011).

[17] P Pärnamets, et al., Biasing moral decisions by exploiting the dynamics of eye gaze. *Proc. National Acad. Sci. U.S.A* **112**, 4170–4175 (2015).

[18] M Ghaffari, S Fiedler, The power of attention: Using eye gaze to predict other-regarding and moral choices. *Psychol. Sci.* **29**, 1878–1889 (2018).

[19] MA Kunar, DG Watson, K Tsetsos, N Chater, The influence of attention on value integration. *Attention, Perception, Psychophys.* **79**, 1615–1627 (2017).

[20] AO Peschel, JL Orquin, SM Loose, Increasing consumers' attention capture and food choice through bottom-up effects. *Appetite* **132**, 1–7 (2019).

[21] S Shimojo, C Simion, E Shimojo, C Scheier, Gaze bias both reflects and influences preference. *Nat. Neurosci.* **6**, 1317–1322 (2003).

[22] C Simion, S Shimojo, Early interactions between orienting, visual sampling and decision making in facial preference. *Vis. Res.* **46**, 3331–3335 (2006).

[23] T Folke, C Jacobsen, SM Fleming, B De Martino, Explicit representation of confidence informs future value-based decisions. *Nat. Hum. Behav.* **1**, 1–8 (2017).

[24] AM Franco-Watkins, JG Johnson, Applying the decision moving window to risky choice: Comparison of eye-tracking and mouse-tracing methods. *Judgm. Decis. Mak.* **6**, 740–749 (2011).

[25] A Rangel, JA Clithero, The computation of stimulus values in simple choice in *Neuroeconomics*, eds. PW Glimcher, E Fehr. (Academic Press, San Diego), Second edition, pp. 125–148 (2014).

[26] JP O'Doherty, U Rutishauser, K Iigaya, The hierarchical construction of value. *Curr. Opin. Behav. Sci.* **41**, 71–77 (2021).

[27] N Stewart, N Chater, GD Brown, Decision by sampling. *Cogn. Psychol.* **53**, 1–26 (2006).

[28] MN Shadlen, D Shohamy, Decision making and sequential sampling from memory. *Neuron* **90**, 927–939 (2016).

[29] JL Orquin, M Wedel, Contributions to attention based marketing: Foundations, insights, and challenges. *J. Bus. Res.* **111**, 85–90 (2020).

[30] UR Karmarkar, H Plassmann, Consumer neuroscience: Past, present, and future. *Organ. Res. Methods* **22**, 174–195 (2019).

[31] OS Collaboration, Estimating the reproducibility of psychological science. *Science* **349** (2015).

[32] JP Ioannidis, Why most published research findings are false. *PLoS Med* **2**, e124 (2005).

[33] JP Simmons, LD Nelson, U Simonsohn, False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychol. Sci.* **22**, 1359–1366 (2011).

[34] R Ratcliff, G McKoon, The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Comput.* **20**, 873–922 (2008).

[35] JI Gold, MN Shadlen, The neural basis of decision making. *Annu. Rev. Neurosci.* **30**, 535–574 (2007).

[36] R Ratcliff, PL Smith, SD Brown, G McKoon, Diffusion decision model: Current issues and history. *Trends Cogn. Sci.* **20**, 260–281 (2016).

[37] M Mormann, JE Russo, Does attention increase the value of choice alternatives? *Trends Cogn. Sci.* **25**, 305–315 (2021).

[38] JH Fecteau, DP Munoz, Salience, relevance, and firing: a priority map for target selection. *Trends Cogn. Sci.* **10**, 382–390 (2006).

[39] JW Bisley, ME Goldberg, Attention, intention, and priority in the parietal lobe. *Annu. Rev. Neurosci.* **33**, 1–21 (2010).

[40] L Itti, C Koch, A saliency-based search mechanism for overt and covert shifts of visual attention. *Vis. Res.* **40**, 1489–1506 (2000).

[41] B Machner, et al., Unbalancing the attentional priority map via gaze-contingent displays induces neglect-like visual exploration. *Front. Hum. Neurosci.* **14**, 41 (2020).

[42] B Machner, et al., Impact of dynamic bottom-up features and top-down control on the visual exploration of moving real-world scenes in hemispatial neglect. *Neuropsychologia* **50**, 2415–2425 (2012).

[43] A Sprenger, D Kömpf, W Heide, Visual search in patients with left visual hemineglect. *Prog. Brain Res.* **140**, 395–416 (2002).

[44] W Heide, D Kömpf, Combined deficits of saccades and visuospatial orientation after cortical lesions. *Exp. Brain Res.* **123**, 164–171 (1998).

[45] M Carrasco, Visual attention: The past 25 years. *Vis. Res.* **51**, 1484–1525 (2011).

[46] KC Armel, A Rangel, The impact of computation time and experience on decision values. *Am. Econ. Rev.* **98**, 163–168 (2008).

[47] F Callaway, A Rangel, TL Griffiths, Fixation patterns in simple choice reflect optimal information sampling. *PLoS Comput. Biol.* **17**, e1008863 (2021).

[48] AI Jang, R Sharma, J Drugowitsch, Optimal policy for attention-modulated decisions explains human fixation behavior. *eLife* **10**, e63436 (2021).

[49] ZW Li, WJ Ma, An uncertainty-based model of the effects of fixation on choice. *PLOS Comput. Biol.* **17**, 1–17 (2021).

[50] EJ Johnson, et al., Beyond nudges: Tools of a choice architecture. *Mark. Lett.* **23**, 487–504 (2012).

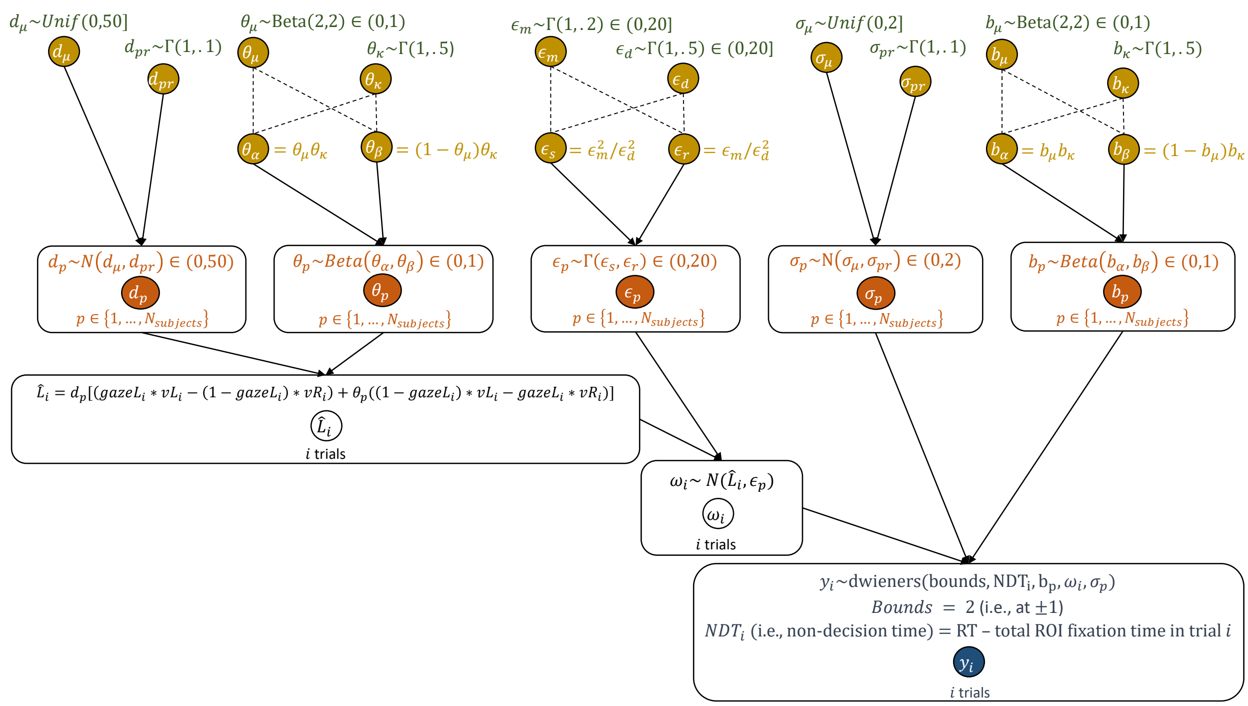
[51] JMT Krijnen, D Tannenbaum, CR Fox, Choice architecture 2.0: Behavioral policy as an implicit social interaction. *Behav. Sci. & Policy* **3**, 1–18 (2017).

[52] G Lombardi, T Hare, Piecewise constant averaging methods allow for fast and accurate hierarchical bayesian estimation of drift diffusion models with time-varying evidence accumulation rates. unpublished (2021).

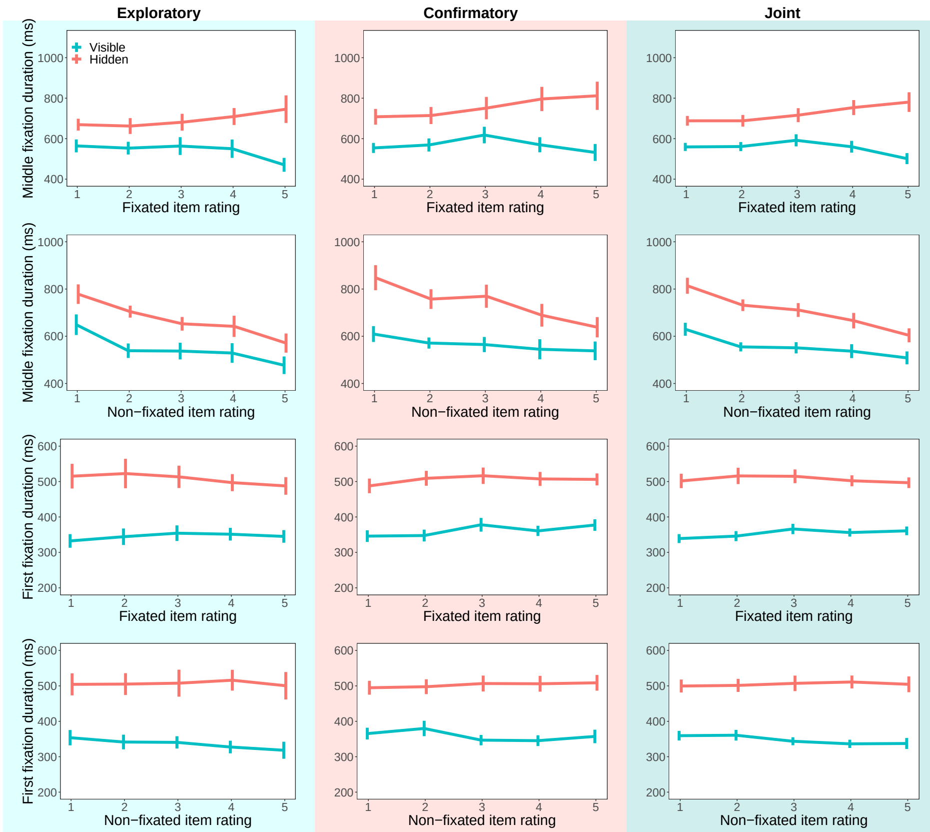
[53] PC Bürkner, brms: An r package for bayesian multilevel models using stan. *J. Stat. Software, Articles* **80**, 1–28 (2017).

[54] PC Bürkner, Advanced bayesian multilevel modeling with the r package brms. *R J.* **10**, 395–411 (2018).

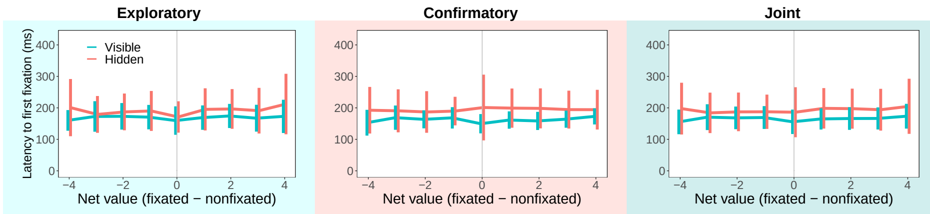
# Supplementary Material



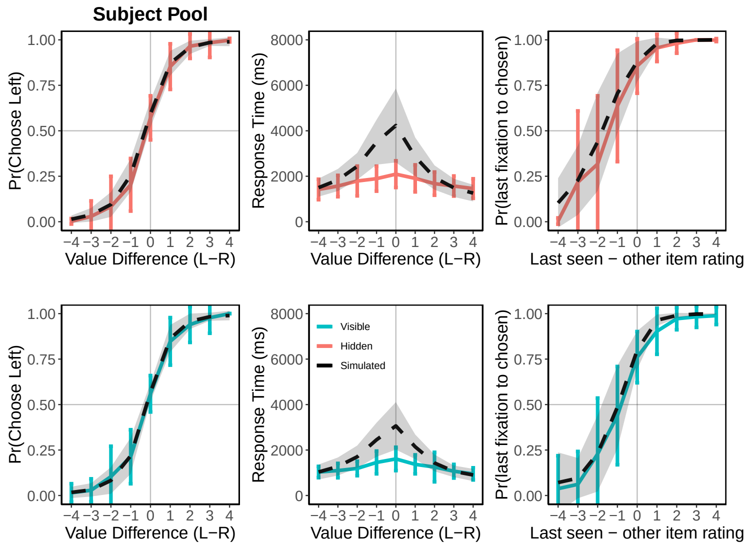

**Supplementary Figure 1: Directed Acyclic Graph of Hierarchical aDDM.** The hierarchical model estimates group and individual parameters. The 10 group parameters are depicted in the top row of yellow circles. The 5 individual parameters estimated for each subject are depicted in orange in the middle row. The distribution of individual parameters as a function of the group parameters is specified using a transformation of some of the parameters, denoted by the dashed lines. The choice and RT outcome $y_i$ of trial $i$ for a subject $p$ is modeled as a Drift-Diffusion-Model with bounds at $\pm 1$, non-decision time $\mathrm{NDT}_i$, bias $b_p$, trial specific slope $\omega_i$, and noise $\sigma_p$. The trial specific slope $\omega_i$ is constructed in two steps. First a trial mean drift rate $\hat{L}_i$ is computed, which depends on the subject's drift rate parameter $d_p$, attentional bias parameter $\theta_p$, gaze data for the trial $gazeL_i$, and item liking ratings for the foods used in the trial ($vL_i$,$vR_i$). $gazeL_i$ denotes the proportion of time spent fixating on the left item during the trial. Second, Gaussian noise $\epsilon_p$ is added to the trial mean drift rate. The hyperpriors for the group parameters are described at the top of the graph. "$\in (X, Y)$" indicates truncation to bounds. $N_{subjects} = 25$ in the exploratory and confirmatory datasets, and 50 in the joint dataset.



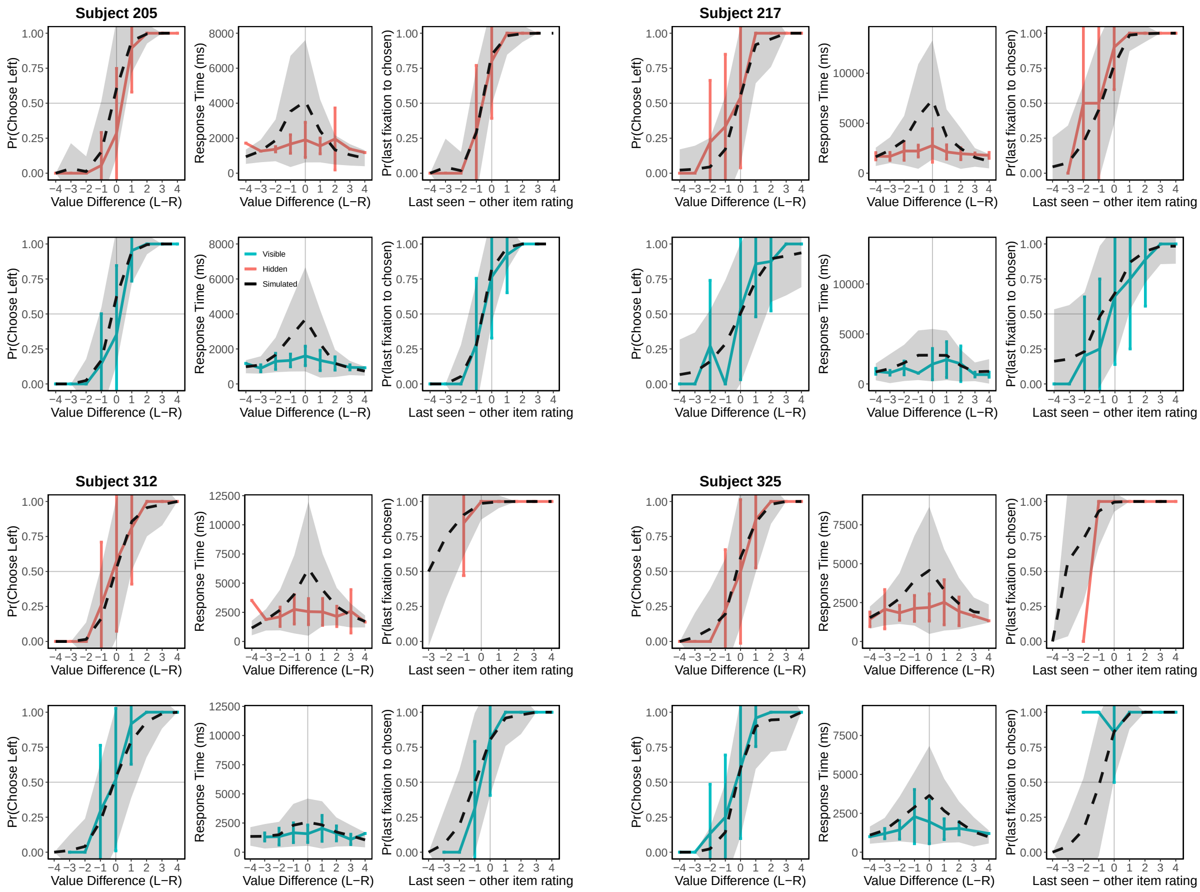

**Supplementary Figure 2: Fixation durations.** *Row 1:* Middle fixation duration as a function of the fixated item rating. *Row 2:* Middle fixation duration as a function of the nonfixated item rating. *Row 3:* First fixation duration as a function of the fixated item rating. *Row 4:* First fixation duration as a function the nonfixated item rating. Columns indicate which dataset generated the figures. Bars denote SEs.




**Supplementary Figure 3:** Latency to first fixation as a function of the relative rating of the fixated item. Columns indicate which dataset generated the figures. Bars denote SDs.




**Supplementary Figure 4: Group level predictions in the joint dataset.** We use the estimates of the hierarchical aDDM in the odd trials to make predictions out-of-sample, in the even trials, separately for each subject and condition. For each subject, we simulate 10 observations per trial, and compare the simulated and observed data. *Blue lines:* Behavior in the visible treatment. *Red lines:* Behavior in the hidden treatment. Bars denote SD. *Black dashed lines and grey areas:* Simulated behavior for the respective treatment (dash = mean, grey = SD).




**Supplementary Figure 5: Subject-level simulations.** Out-of-sample predictions versus data for four randomly selected subjects. See Figure S4 and Methods for details. *Blue lines:* Behavior in the visible treatment. *Red lines:* Behavior in the hidden treatment. Bars denote SD. *Black dashed lines and grey areas:* Simulated behavior for the respective treatment (dash = mean, grey = SD).

| | | Exploratory | | | Confirmatory | | | Joint | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dept. Var. | Indept. Var. | Est. | SE | | Est. | SE | | Est. | SE | |
| Left chosen | Intercept | 0.11 | 0.08 | | 0.03 | 0.04 | | 0.07 | 0.04 | |
| (Logistic) | L - R rating | 1.57 | 0.12 | * | 1.69 | 0.15 | * | 1.63 | 0.10 | * |
| (Top) | Hidden | -0.03 | 0.09 | | 0.09 | 0.06 | | 0.03 | 0.05 | |
| | Interaction | 0.20 | 0.10 | * | 0.08 | 0.08 | | 0.12 | 0.06 | * |
| RT | Intercept | 1493.74 | 95.84 | * | 1750.60 | 123.34 | * | 1626.86 | 78.27 | * |
| (Linear) | Best - worst rat. | -172.72 | 25.56 | * | -212.01 | 26.43 | * | -192.77 | 18.14 | * |
| (Middle) | Hidden | 541.84 | 76.92 | * | 494.53 | 96.57 | * | 516.62 | 61.75 | * |
| | Interaction | -13.29 | 19.26 | | -31.78 | 30.57 | | -21.68 | 17.46 | |
| # of fix. | Intercept | 2.83 | 0.09 | * | 3.18 | 0.10 | * | 3.01 | 0.07 | * |
| (Linear) | Best - worst rat. | -0.20 | 0.02 | * | -0.27 | 0.02 | * | -0.23 | 0.02 | * |
| (Bottom) | Hidden | -0.02 | 0.07 | | -0.21 | 0.10 | * | -0.11 | 0.06 | |
| | Interaction | 0.05 | 0.02 | * | 0.09 | 0.03 | * | 0.07 | 0.02 | * |

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

**Supplementary Table 1:** Regressions associated with the basic psychometric results in Fig. 2

| | | Exploratory | | | Confirmatory | | | Joint | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dept. Var. | Indept. Var. | Est. | SE | | Est. | SE | | Est. | SE | |
| 1st fix. best | Intercept | 0.14 | 0.06 | * | -0.10 | 0.05 | | 0.01 | 0.04 | |
| (Logistic) | Best - worst rat. | -0.04 | 0.03 | | 0.04 | 0.03 | | 0.00 | 0.02 | |
| (Row 1) | Hidden | -0.16 | 0.09 | | 0.13 | 0.07 | | 0.00 | 0.06 | |
| | Interaction | 0.05 | 0.05 | | -0.06 | 0.04 | | -0.02 | 0.03 | |
| Mid. fix. dur. | Intercept | 579.57 | 34.69 | * | 566.08 | 34.15 | * | 575.56 | 22.24 | * |
| (Linear) | Fix. - nonfix. rat. | -23.00 | 7.25 | * | -27.74 | 6.67 | * | -24.73 | 4.86 | * |
| (Row 3) | Hidden | 108.49 | 27.18 | * | 140.97 | 27.98 | * | 147.22 | 19.86 | * |
| | Interaction | -18.39 | 9.55 | | -16.09 | 11.62 | | -22.05 | 7.94 | * |
| 1st fix. dur. | Intercept | 341.02 | 20.83 | * | 356.97 | 15.99 | * | 348.50 | 12.64 | * |
| (Linear) | Fix. - nonfix. rat. | -1.41 | 1.54 | | -1.01 | 1.88 | | -1.05 | 1.10 | |
| (Row 4) | Hidden | 157.49 | 22.95 | * | 147.24 | 19.69 | * | 154.55 | 14.88 | * |
| | Interaction | 4.95 | 2.68 | | -0.59 | 2.38 | | 2.26 | 1.80 | |
| Net fix. dur. | Intercept | -14.29 | 28.94 | | 12.39 | 20.64 | | 3.43 | 17.09 | |
| (Linear) | Net. Val. > 0 (A) | 44.58 | 36.71 | | 16.61 | 26.53 | | 24.65 | 22.15 | |
| (Row 5) | Net. Val. < 0 (B) | -24.24 | 32.08 | | -58.30 | 31.24 | | -44.87 | 22.15 | * |
| | A : Net. Val. (C) | 26.63 | 11.18 | * | 11.36 | 9.25 | | 19.56 | 6.95 | * |
| | B : Net. Val. (D) | 40.50 | 11.07 | * | 26.68 | 9.78 | * | 34.06 | 7.61 | * |
| | Hidden (E) | -20.06 | 43.95 | | -25.97 | 40.50 | | -24.07 | 30.72 | |
| | A:E | 80.39 | 44.06 | | 68.01 | 47.63 | | 77.19 | 32.16 | * |
| | B:E | -41.94 | 47.20 | | -101.36 | 40.82 | * | -69.12 | 32.63 | * |
| | C:E | 7.35 | 17.09 | | 5.76 | 13.80 | | 6.25 | 11.40 | |
| | D:E | -5.10 | 14.84 | * | -34.00 | 13.45 | * | -19.85 | 9.94 | * |

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

**Supplementary Table 2:** Regressions associated with the fixation results in Fig. 3

| | | Exploratory | | | Confirmatory | | | Joint | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dept. Var. | Indept. Var. | Est. | SE | | Est. | SE | | Est. | SE | |
| Mid. fix. dur. | Intercept | 588.86 | 36.14 | * | 567.52 | 28.80 | * | 575.98 | 22.07 | * |
| (Linear) | Fix. rating | -11.72 | 7.78 | | 1.71 | 8.38 | | -3.97 | 5.74 | |
| (Row 1) | Hidden | 62.00 | 29.36 | * | 85.85 | 28.16 | * | 78.22 | 20.34 | * |
| | Interaction | 24.06 | 10.72 | * | 29.16 | 10.86 | * | 25.98 | 7.58 | * |
| Mid. fix. dur. | Intercept | 671.57 | 37.98 | * | 653.75 | 28.33 | * | 660.18 | 23.48 | * |
| (Linear) | Nonfix. rating | -42.17 | 6.75 | * | -29.70 | 8.84 | * | -34.36 | 5.75 | * |
| (Row 2) | Hidden | 143.91 | 30.26 | * | 218.50 | 38.36 | * | 193.08 | 25.56 | * |
| | Interaction | -8.43 | 9.47 | | -21.23 | 9.78 | * | -16.72 | 6.64 | * |
| 1st fix. dur. | Intercept | 328.74 | 21.45 | * | 340.25 | 19.94 | * | 334.55 | 14.67 | * |
| (Linear) | Fix. rating | 4.15 | 2.24 | | 5.72 | 3.43 | | 5.15 | 1.99 | * |
| (Row 3) | Hidden | 188.85 | 30.79 | * | 157.49 | 23.07 | * | 176.50 | 19.69 | * |
| | Interaction | -10.11 | 4.70 | | -3.47 | 3.62 | | -7.23 | 3.05 | * |
| 1st fix. dur. | Intercept | 359.25 | 21.13 | * | 373.21 | 17.49 | * | 366.87 | 13.65 | * |
| (Linear) | Nonfix. rating | -6.56 | 2.20 | * | -6.48 | 2.04 | * | -6.47 | 1.45 | * |
| (Row 4) | Hidden | 138.82 | 24.63 | * | 127.21 | 20.19 | * | 133.35 | 15.52 | * |
| | Interaction | 9.90 | 3.22 | * | 7.60 | 2.96 | * | 8.68 | 2.13 | * |

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

**Supplementary Table 3:** Regressions associated with the fixation duration results in Fig. S2

| | | Exploratory | | | Confirmatory | | | Joint | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dept. Var. | Indept. Var. | Est. | SE | | Est. | SE | | Est. | SE | |
| Latency to 1st fix. | Intercept | 167.07 | 8.46 | * | 157.19 | 6.92 | * | 162.58 | 5.37 | * |
| (Linear) | Fix. - nonfix. rating | -0.89 | 3.30 | | 1.46 | 4.36 | | 0.22 | 3.65 | |
| | Hidden | 3.70 | 4.41 | | 5.05 | 4.85 | | 8.17 | 4.34 | |
| | Interaction | 1.05 | 3.90 | | 0.87 | 4.54 | | 2.13 | 3.96 | |

* indicates significance in all data sets at the 95% confidence level.
* indicates a significant effect that was not present in all three data sets.

**Supplementary Table 4:** Regressions associated with the first fixation latency results in Fig. S3

| | | Exploratory | | | Confirmatory | | | Joint | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dept. Var. | Indept. Var. | Est. | SE | | Est. | SE | | Est. | SE | |
| Left chosen | Intercept | -0.68 | 0.16 | * | -1.58 | 0.26 | * | -1.12 | 0.16 | * |
| (Logistic) | Left - right rating (A) | 1.54 | 0.14 | * | 1.75 | 0.18 | * | 1.64 | 0.11 | * |
| (Top) | Last fix. loc. (0=R,1=L;B) | 1.82 | 0.31 | * | 3.18 | 0.48 | * | 2.47 | 0.29 | * |
| | Hidden (C) | -1.21 | 0.31 | * | -1.46 | 0.36 | * | -1.32 | 0.23 | * |
| | A:B | 0.15 | 0.12 | | -0.14 | 0.13 | | -0.01 | 0.08 | |
| | A:C | 0.28 | 0.15 | * | -0.18 | 0.18 | | 0.08 | 0.09 | |
| | B:C | 3.76 | 0.64 | * | 3.83 | 0.61 | * | 3.69 | 0.43 | * |
| | A:B:C | -0.59 | 0.23 | * | 0.14 | 0.25 | | -0.25 | 0.15 | |
| Corr. left chosen | Intercept | 0.00 | 0.01 | | 0.00 | 0.00 | | 0.00 | 0.00 | |
| (Linear) | Net fixation left (s) | 0.25 | 0.04 | * | 0.24 | 0.04 | * | 0.23 | 0.03 | * |
| (Middle) | Hidden | 0.00 | 0.01 | | 0.01 | 0.01 | | 0.01 | 0.01 | |
| | Interaction | 0.04 | 0.04 | | 0.04 | 0.03 | | 0.04 | 0.02 | |
| Corr. last chosen | Intercept | -0.06 | 0.02 | * | -0.08 | 0.02 | * | -0.07 | 0.01 | * |
| (Linear) | First fixation duration (s) | 0.15 | 0.05 | * | 0.20 | 0.06 | * | 0.19 | 0.04 | * |
| (Bottom) | Hidden | 0.05 | 0.02 | | 0.04 | 0.03 | | 0.04 | 0.02 | * |
| | Interaction | -0.16 | 0.05 | * | -0.14 | 0.06 | * | -0.15 | 0.04 | * |

* indicates significance in all data sets at the 95% confidence level.

* indicates a significant effect that was not present in all three data sets.

**Supplementary Table 5:** Regressions associated with choice bias results in Fig. 4