Within-Domain and Cross-Domain Effects of Choice-Induced Bias

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Abstract Recent evidence suggests choices influence evaluation, giving rise to choice-induced bias. It is however unknown whether this phenomenon is constrained to the domain of choice, or spans across domains, allowing a decision to influence evaluation of unrelated item-specific information. In a set of 5 experiments (4 preregistered, total of 425 participants) we show that people can be influenced by their choices not only when the choices are relevant to the evaluation (within-domain), but also when they are not (across-domains), and explore the differences between the two. Our generative model reveals that the bias is driven jointly by two mechanisms: a domain-general, conflict-sensitive consistency bias, and a domain-specific value-update. These two mechanisms can be mapped into two prevalent theories of choice-induced bias: cognitive dissonance, and self-perception theory.

Keywords choice-induced bias · value updating · consistency bias · cognitive modelling ·

Introduction

According to economic theory, choices are a passive reflection of underlying preferences [1]. This view has been challenged by psychological research, show-

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ing choices have a causal power over preferences [2,3,4,5] leading to a positive feedback loop: the more an option is chosen, the greater its value, the more likely it is to be chosen in the future.

Choice-induced bias (CIB) have been demonstrated in different domains (subjective preference: [3,5,6,7], perception: [8,9,10], higher cognitive inference [10,11]), and across timeframes, from immediate, trial-level effects [11,12], to long-lasting changes in preference [13]. CIB can affect both cognitive representations [14,15,16] and neural activity [17,18,19,20]. Combined, these findings suggest that the phenomenon is robust. It remains unclear however whether the effect found in perceptual studies is driven by similar mechanisms to that described in the preference literature.

The comparison of the CIB between different domains prompts a critical question: is it possible for the bias to transfer from one domain to another? For example, a hypothetical voter is motivated to vote for candidate *A* over candidate *B* due to his charisma. Firstly, the act of choice (vote) can further widen the gap in perceived charisma in favour of the chosen candidate. This is a classic case of CIB, where the affected beliefs are causally associated with the domain of choice (*"I find candidate A more charismatic, therefore I vote for him, which leads me to find him even more charismatic"*). Additionally, the vote could potentially affect how one views the candidates in unrelated domains, such as proposed policies (*"I find candidate A more charismatic, therefore I vote for him, which leads me to view his policies more favourably"*). We refer to these as a *within-domain*, and *cross-domain* effects, respectively.

CIB has been commonly associated with two alternative mechanisms: a motivated conflict resolution *via* dissonance reduction [21,22,23,24], or inferring value based on ones own choices [9,19,25,26]. The first mechanism stems from cognitive dissonance theory [27], arguing that people are intrinsically motivated to keep an internal consistency between their choices and judgments, even when facing contradictory evidence. The second proposal originates from Bem's self-perception theory [28] and argues for an epistemic interpretation [29] where conflict or an affective experience are unnecessary, and the bias reflects choice-driven expectancy update [30] or inference based on the explicit memory of previous choices (*"I remember choosing it, so I must like it"*). While most studies implicitly frame these explanations as exclusive, there is no reason to assume they cannot jointly contribute to the CIB effect. An abundance of evidence for both suggests that this is in fact a strong possibility. To our knowledge however, no studies attempted to distinguish the contributions of both mechanisms.

Here, we compare the behavioral effects and cognitive mechanisms of CIB *between* and *across* preference and perceptual domains in a set of 5 experiments. We use a task where choices between 2 items in either domain are immediately followed by a comparative judgment of the same two items on a continuous scale, reflecting the difference in their value estimations. The design allows us to test both within-domain (when choice and judgment domains are consistent across the trial) and cross-domain effects (when choice and judg-

ment are inconsistent across the trial; *e.g.* size choice followed by preference judgment).

We model the generative process, distinguishing between two mechanisms responsible for the bias: a consistency-driven domain-general effect which affects immediate evaluation but has no effect on the underlying values, and a domain-sensitive value-update mechanism. First of the proposed mechanisms, the consistency-driven effect, is similar to the time-dependency effects found in many perceptual studies, where a choice modulates the gain of upcoming sensory information [10, 11, 31], and can be related to the cognitive dissonance theory. In this view, the choice conflict and importance elevate experienced discomfort [32, 33], which can be reduced by adjusting one's expectations in favour of the chosen option or against the rejected one. The value-update mechanism, on the other hand, is a rational update of one's beliefs based on remembered choices, similar to a reinforcement learning mechanism [34, 25] with implicit rewards. The rationale being that one can learn their own preferences in a similar way they can learn the structure of the surrounding environment.

Two crucial factors that differentiate the two explanations are context-sensitivity and effect longevity. If the bias is driven by a need for choice consistency irrespective of the context, one might expect it to be domain-general, *i.e.*, independent of the type of choice, as well as short-lived, as consistency exhibited in the past no longer holds relevance when future choices are made. In contrast, value-sensitive updates should be sensitive to the domain of choice (person's preference-based choices should ideally affect only his preference values, but not perceptual estimations, and *vice versa*) while its temporal effects are constrained by one's memory capacity for previous choices.

In Experiments 1 (lab-based study) and 2 (large-scale online replication) we (a) establish the existence of a prevalent cross-domain CIB, and (b) compare the qualitative (driving factors) and quantitative (effect sizes) differences between within and cross domain effects in preference and perception, testing the effects of choice difficulty, or conflict [35, 18] and magnitude, or importance [4].

In Experiment 3, we introduce a forced-choice condition to test whether exogenously driven choices can also induce CIB. Voluntariness of choice have been postulated to be necessary for a CIB to occur in preference-based tasks [36, 2], it has however not been systematically compared across domains.

In Experiment 4, we modify the task by replacing one of the items after each choice but before judgment in order to compare to what extent is the effect driven by overvaluing the chosen item compared to undervaluing the rejected one. Previous research in this area was done only in preference literature, and provided inconsistent results, from undervaluation effects being stronger [22, 18], both being roughly equal [6, 37, 38] to overvaluation being stronger [2].

In Experiment 5 we manipulate which item should be considered the 'default' (so called *reference* item) to which the other is compared during the judgment phase. This manipulation accounts for one possible source of the bias - a bias towards the status quo [39]. If the chosen item is considered the reference, CIB could be explained by information sampling biased towards

positive evidence [40]. In this view, participants use their choice as an implicit reference, which drives the bias. By explicitly manipulating the reference item during the judgment phase we can dissociate between the effects of choice and reference.

Finally, we fit a generative model to distinguish between two processes giving rise to CIB: a consistency-driven domain-general effect (consistency bias; CB), and a domain-sensitive value-update (VU), related to cognitive dissonance reduction [27] and self-perception theory [28] respectively. We find that, consistent with the theoretical conceptualization, CB affects both *within* and *cross* conditions, while VU is specific to *within-domain* CIB.

Results

Participants performed a 2-step task in which they made 2-alternative forced choices, followed by judgments of difference between the item values on a continuous scale (see Figure 4). Choices and judgments could belong to either perceptual (size) or preference domains. Additionally, on some trials participants only examined the items without making a choice (no-choice condition).

Before the task, participants rated each item separately on a 100-point scale in terms of subjective preference and estimated size (percent of non-white pixels), twice in each domain. Averaged rating in each category provided a baseline value estimate for item preference and size estimate. After the task, participants rated all items once more.

In Experiment 3, no-choice trials were substituted with a forced-choice condition, where participants had to choose the item instructed by the computer. In Experiment 4, one of the items was replaced by a different one between the choice and judgment. In Experiment 5, during the judgment, one of the items was marked as the reference, so that the judgment was made relative to it.

Consistency and Performance Quality

We assume that the initial ratings are a consistent and unbiased measure of individual value estimation. To verify this, we tested *a)* the consistency between a set of objective and task-derived measures and the initial ratings, and *b)* how consistent task performance was in relation to the initial estimations.

We correlated judgments with objective item sizes using Spearman’s rank correlation coefficient (r_s) per session (Experiment 1) or *per* participant (Experiments 2-5). Size estimations were reflective of actual item size rank order (all $p < 0.001$): $M = 0.85$, $SD = 0.14$ (Experiment 1); $M = 0.66$, $SD = 0.19$ (Experiment 2); $M = 0.69$, $SD = 0.16$ (Experiment 3); $M = 0.64$, $SD = 0.22$ (Experiment 4); $M = 0.63$, $SD = 0.19$ (Experiment 5). High accuracy in item size ranking indicates good understanding of the task requirements.

Pre-task and post-task ratings were significantly correlated with one another (all $p < 0.001$): $M_{\text{pref}} = 0.81$, $SD_{\text{pref}} = 0.14$, $M_{\text{size}} = 0.78$, $SD_{\text{size}} = 0.19$

Fig. 1 . Behavioural Results. a) Visualization of the main findings: right-bias as a function of choice and trial type in Experiment 1 (left), choice induced bias across trial types (error bars represent standard errors) in Experiments 1 (upper right) and 2 (lower right). Red and blue represent preference and size domains respectively. b) Posterior group parameter estimations for main predictors across Experiments 1 & 2. Gray area represents Region of Practical Equivalence (ROPE). c) Posterior group parameter estimations for crucial predictors in Experiments 3-5. Gray area represents ROPE, red and blue represent preference and size domains respectively.

(Experiment 1); $M_{\text{pref}} = 0.85$, $SD_{\text{pref}} = 0.13$, $M_{\text{size}} = 0.73$, $SD_{\text{size}} = 0.19$ (Experiment 2); $M_{\text{pref}} = 0.86$, $SD_{\text{pref}} = 0.10$, $M_{\text{size}} = 0.73$, $SD_{\text{size}} = 0.16$ (Experiment 3); $M_{\text{pref}} = 0.81$, $SD_{\text{pref}} = 0.20$, $M_{\text{size}} = 0.73$, $SD_{\text{size}} = 0.16$ (Experiment 4); $M_{\text{pref}} = 0.85$, $SD_{\text{pref}} = 0.14$, $M_{\text{size}} = 0.73$, $SD_{\text{size}} = 0.14$ (Experiment 5).

Choice consistency was defined as the percentage of times the item which was rated as more valuable on a given scale was chosen. We calculated choice consistency *per* participant in each experiment ($p < 0.001$ for all comparisons using a one-sample t-test against chance-level): $M_{\text{pref}} = 77.7\%$, $SD_{\text{pref}} = 6.9\%$, $M_{\text{size}} = 79.7\%$, $SD_{\text{size}} = 6.0\%$ (Experiment 1); $M_{\text{pref}} = 71.3\%$, $SD_{\text{pref}} = 11.0\%$, $M_{\text{size}} = 76.7\%$, $SD_{\text{size}} = 10.0\%$ (Experiment 2); $M_{\text{pref}} = 73.0\%$, $SD_{\text{pref}} = 8.7\%$, $M_{\text{size}} = 76.4\%$, $SD_{\text{size}} = 9.3\%$ (Experiment 3); $M_{\text{pref}} = 71.5\%$, $SD_{\text{pref}} = 9.3\%$, $M_{\text{size}} = 75.1\%$, $SD_{\text{size}} = 12.4\%$ (Experiment 4); $M_{\text{pref}} = 73.0\%$, $SD_{\text{pref}} = 11.6\%$, $M_{\text{size}} = 73.0\%$, $SD_{\text{size}} = 9.8\%$ (Experiment 5).

To assess judgment consistency, we binarized the judgments (negative values indicate judgment towards the left item; positive towards the right) and then, similarly to choice consistency, calculated the percentage of judgments consistent with the initial ratings ($p < 0.001$ for all comparisons using a one-sample t-test against chance-level): $M_{\text{pref}} = 83.3\%$, $SD_{\text{pref}} = 6.0\%$, $M_{\text{size}} = 84.1\%$, $SD_{\text{size}} = 6.4\%$ (Experiment 1); $M_{\text{pref}} = 73.0\%$, $SD_{\text{pref}} = 11.0\%$, $M_{\text{size}} = 76.9\%$, $SD_{\text{size}} = 11.0\%$ (Experiment 2); $M_{\text{pref}} = 76.1\%$, $SD_{\text{pref}} = 9.7\%$, $M_{\text{size}} = 78.4\%$, $SD_{\text{size}} = 9.7\%$ (Experiment 3); $M_{\text{pref}} = 72.7\%$, $SD_{\text{pref}} = 9.5\%$, $M_{\text{size}} = 76.7\%$, $SD_{\text{size}} = 12.2\%$ (Experiment 4); $M_{\text{pref}} = 72.6\%$, $SD_{\text{pref}} = 12.2\%$, $M_{\text{size}} = 72.8\%$, $SD_{\text{size}} = 11.3\%$ (Experiment 5).

Overall, high consistency measures indicate that participants understood the task and their initial value estimations were relatively stable across the length of the experiment. Additional analyses related to the correlations between preference and size ratings can be found in the *Supplementary Materials*.

Main behavioural findings

Across and Within-Domain CIB.

In both Experiments 1 (lab-based) and 2 (online), we found overwhelming evidence for the existence of choice-induced bias $med = 26.63$, 95% CI [22.01, 31.72], $pd > 0.999$, 0% in ROPE (Experiment 1), $med = 31.90$, 95% CI [30.03, 33.80], $pd > 0.999$, 0% in ROPE (Experiment 2). The main effect was larger for within-domain compared to cross-domain conditions $med = 17.63$, 95% CI [12.47, 21.98], $pd > 0.999$, 0% in ROPE (Experiment 1), $med = 22.95$, 95% CI [20.89, 25.07], $pd > 0.999$, 0% in ROPE (Experiment 2), and for preference judgments $med = 7.78$, 95% CI [4.42, 10.82], $pd > 0.999$, 0% in ROPE (Experiment 1), $med = 8.54$, 95% CI [6.77, 10.55], $pd > 0.999$, 0% in ROPE (Experiment 2). Bias was also significantly driven by congruent judgment difficulty (absolute difference in estimated value between items) $med = 8.94$, 95% CI [6.96, 10.69] $pd > 0.999$, 0% in ROPE (Experiment 1), $med = 5.16$, 95% CI [4.52, 5.87] $pd > 0.999$, 0% in ROPE (Experiment 2). and the congruent judgment magnitude (sum of the item values) $med = 3.59$, 95% CI [2.13, 5.01],

pd > 0.999, 1.57% in ROPE (Experiment 1), $med = 3.24$, 95% CI [0.18, 1.77],
pd > 0.999, 0.20% in ROPE (Experiment 2).

We did not find sufficient evidence for the influence of the difficulty or magnitude of the incongruent domain $med_{\text{Difficulty-across}} = 0.10$, 95% CI [-1.37, 1.71], pd = 0.56 (Experiment 1) $med_{\text{Difficulty-across}} = 1.58$, 95% CI [0.60, 2.46], pd = 80.0, 100% in ROPE (Experiment 2) $med_{\text{Magnitude-across}} = -1.30$, 95% CI [-2.42, -0.22], pd = 98.9 (Experiment 1), 89.92% in ROPE (Experiment 1), $med_{\text{Magnitude-across}} = 0.93$, 95% CI [0.18, 1.77], pd = 98.9 (Experiment 2), 99.38% in ROPE (Experiment 2). The effect of domain was only present in the within-domain conditions $med_{\text{congruency_x_domain}} = 7.78$, 95% CI [4.42, 10.82], pd > 0.999, 0% in ROPE (Experiment 1), $med_{\text{congruency_x_domain}} = 8.54$, 95% CI [6.77, 10.55], pd > 0.999, 0% in ROPE (Experiment 2). Congruent difficulty had a stronger effect in the within-domain conditions $med_{\text{congruency_x_domain}} = 5.69$, 95% CI [4.56, 6.82], pd > 0.999, 0% in ROPE (Experiment 1) $med_{\text{congruency_x_domain}} = 6.94$, 95% CI [4.49, 9.22], pd > 0.999, 0% in ROPE (Experiment 2) indicating choice conflict had a significant effect on subsequent judgment. Similarly, congruent magnitude influenced judgment more strongly in the within-domain trials $med_{\text{congruency_x_domain}} = 2.16$, 95% CI [0.93, 3.32], pd > 0.999, 39.73% in ROPE (Experiment 1), $med_{\text{congruency_x_domain}} = 2.32$, 95% CI [1.38, 3.29], pd > 0.999, 26.07% in ROPE (Experiment 2).

Confound analysis

An alternative interpretation of CIB is that it can arise spontaneously due to a regression to the mean, effectively revealing true preferences and beliefs, instead of shaping them [41,42]. To account for this effect, we performed an extensive set of simulations, varying parameters related to the ratings, choices and judgments (*Supplementary Materials*), which revealed that given a reasonable set of assumptions a large bias is extremely unlikely to arise due to this confound. In all but the most extreme parameter settings within-domain CIB was not larger than 1 point (0.5% of the judgment scale), while the cross-domain effect was centered at 0 (see: *Simulation* section in the *Supplementary Materials*).

The Need for Voluntary Choices

To test the effect of voluntary choice on CIB, Experiment 3 introduced forced-choice control condition (Figure 4c) in which participants were instructed to choose a specified item. In contrast to voluntary decision conditions which replicated findings from our previous experiments (Figure 1c), the bias following forced choices was not significantly different from 0: $med = 1.08$ 95% CI [-1.29, 3.43], pd = 0.77 suggesting that a voluntary choice is necessary for the bias to occur.

Overestimation vs Underestimation

In Experiment 4, we tested to what extent is the bias driven by overvaluation the chosen option, as compared to undervaluing the rejected one. For this purpose, one of items (either the chosen or rejected) was replaced after each choice (Figure 4c). We found a modest yet significant effect of item replacement, $med_{\text{rejected-chosen}} = 1.89$, $CI = [0.09, 3.75]$, $pd = 0.98$, 53.85% in ROPE (Figure 1c), indicating that the undervaluation of the rejected item being stronger than overvaluation of the chosen one.

Positive reference effects

To isolate the positive reference effect, we looked at reference bias in no-choice trials, finding a strong effect of positive reference on judgment $med = 11.81$, 95% $CI [6.88, 17.02]$, $pd > 0.999$, 0.02% in ROPE.

Then, we analyzed whether the choice-induced effect prevailed in choice trials. No-choice condition served as a baseline for reference bias, to which all other trials types were compared to. This enabled to estimate the effect of choice independent of the frame of reference $med = 36.00$, 95% $CI [30.34, 41.29]$, $pd > 0.999$, 0% in ROPE. The differences in choice-induced bias between reference-chosen and reference-rejected conditions after removing reference baseline were non-significant $med = 4.51$, 95% $CI [-1.70, 11.12]$, $pd = 0.91$.

Generative Modelling

To understand the generative processes giving rise to the choice-induced bias, we built a hierarchical Bayesian model introducing two potential sources of CIB: a domain-general consistency bias and a domain-specific value update (see: *Methods*), and fitted it to the data from Experiment 2. We tested 4 models with varying assumptions: *Null* (stable values; no sources of CIB present in data generating process), *Consistency-Only*, *Update-Only* and *Full* (both sources of CIB present). Model comparison using Leave-One-Out Information Criterion [43] indicated that the full model fitted the data best $LOO = 269.9$, $SE = 29.4$, $P_{\text{best}} > 0.999$ based on Bayesian model averaging [44] (Figure 2b). Strong correlations (per participant) between model-derived final value predictions and post-task ratings $M = 0.750$, $SD = 0.226$ for preference and $M = 0.739$ $SD = 0.228$ for size indicated the model can predict the final ratings well. Compared to the initial ratings, model-derived values predicted the final ratings more accurately: $M_{\text{Delta}R^2} = 0.11$, $t(243) = 7.80$, $p < 0.001$ for preference and $M_{\text{Delta}R^2} = 0.03$, $t(243) = 2.878$, $p = 0.002$ for size (Figure 2c).

Consistency Bias. The winning model displayed a consistency effect $med = 0.065$ 95% $CI [0.055, 0.076]$, $pd > 0.999$, which was modulated by decision conflict $med = 0.029$ 95% $CI [0.023, 0.033]$, $pd > 0.999$.

Fig. 2 Generative model fitting. a) An instance of dynamic value updating for a single item. The internal value fluctuates as a function of choices. Green points show trials where item was chosen; red when it was rejected. b) Model comparison. Upper panel shows relative LOOIC scores, error bars represent SE. Lower panel shows the probabilities of each model providing the best fit based on Bayesian Model Averaging of LOOIC scores (Yao et al., 2018). c) Posterior Predictive model validation for choices (left) and judgments (right) in terms of R^2 . Each dot represents a single participant. d) Out-of-sample (OOS) model-derived prediction of final ratings (Y-axis) plotted against prediction derived from initial ratings for preference (left) and size (right). P-values indicate that model-based prediction was significantly better.

Value Update. Within-domain update parameter values were all greater than 0 with $pd > 0.999$: positive preference-within update $med = 0.058$, 95% CI [0.049, 0.067]; negative preference-within update $med = 0.138$, 95% CI [0.126, 0.152]; positive size-within update $med = 0.019$, 95% CI [0.013, 0.026]; negative size-within update $med = 0.093$, 95% CI [0.084, 0.105];

Cross-domain parameter updates were all smaller than 0.01 (1% of item value), suggesting their nature is inconsequential for the observed bias: positive preference-across update $med = -0.004$, 95% CI [-0.010, 0.002], $pd = 0.09$; negative preference-across update $med = 0.001$, 95% CI [0.001, 0.015], $pd = 0.99$; positive size-across update $med = -0.006$, 95% CI [-0.011, -0.001], $pd =$

Fig. 3 Parameters of the best fitting model. α and β represent the positive and negative updates, respectively.

0.99; negative size-across update $med = 0.006$, 95% CI [0.000, 0.011], $pd = 0.97$;

Value Discounting. Parameter k values were close to 0 $med = 0.009$, 95% CI [0.006, 0.012] indicating only marginal decay.

Discussion

People’s judgments are biased by their choices. In a suite of 5 experiments, we show that this phenomenon is not only ubiquitous within perceptual and preference domains, but also that choices of one type can affect evaluation in an unrelated domain. Our findings bridge the literature on CIB in perception and preference which, up to this point, have been studied separately.

Our main findings demonstrate the existence of a cross-domain CIB, whose strength was consistent across all experiments. Cross-domain effects are especially interesting, as they illustrate a clear deviation from optimality: there is no apparent reason as for how such bias could be beneficial for the agent, challenging hypotheses postulating an adaptive role of CIB [45,46,47,29,48]. While within-domain effects can be explained by value inference conditioned on one’s choices [28,29], similar interpretation is irrelevant in the context of cross-domain effects, suggesting a prioritization of consistency at the cost of accuracy. One potential mechanism for a similar effect have been also recently proposed by Horsby and Love [49], who suggest that all relevant dimensions of a choice option are represented in a shared, continuous space, where values are updated through coherency optimization. The model however does not tackle representations of inherently objective dimensions, such as assessment of perceptual attributes.

We found within-domain effects in preference and perception to be influenced by choice difficulty (how close in value the items are) and magnitude (the sum of item values). Conflict-driven bias has been shown to influence dissonance resolution after preference-based choice [50,18,51]. Magnitude (or *value sensitivity*, [52]) is known to influence choices [53,54,55] as well as confidence [56], suggesting that absolute value of choice options inflates decision noise but reduces uncertainty. In the context of CIB, effects of magnitude have been postulated as potentially influencing the post-choice alternative spread [27]. This claim has previously met with mixed evidence [57]. Our experiments offer new evidence, suggesting that magnitude can be incorporated naturally into the value-update mechanism *via* proportional updates.

In a set of additional experiments, we tested a set of alternative explanations and constraints of the CIB effect. In Experiment 3 we find no effect of involuntary choices on CIB. This finding is consistent with the preference literature [2], and shows that a simple motor action is not enough for the bias to occur. Rather, consistent with an action-driven theory of CIB [46], a voluntary choice is necessary. Additionally, this result supports the claim that CIB is not a result of a simple motor bias towards the just performed action due to motor costs associated with switching [58].

In Experiment 4, we tested the bias related to chosen and rejected items separately. Previous literature on post-choice dissonance produced a set of inconsistent results with regards to this issue, from undervaluation effects being stronger, [22,18], both being roughly equal [6,37,38] to overvaluation being stronger [2]. Our results indicate that both processes may contribute to a similar extent, with a small but significant difference in favour of rejected item devaluation being stronger than chosen item overvaluation. Additionally, the design allowed us to test a potential attentional confound. Visual attention can bias evidence accumulation in favor of the fixated item [59]. If attention is biased towards the chosen item which in turn drives the CIB effect, then we should observe a significant reduction of CIB when the chosen item is replaced with an alternative, compared to when it remains on the screen, which was not the case.

In Experiment 5, we tested an alternative interpretation of CIB that is unrelated to conflict-driven processing or value updating, and can be referred to as the positive evidence [40], or reference effect. Assuming participants treat the chosen option as the default, a bias could arise due to uneven weighting of positive (pro-choice) vs negative evidence. By controlling for which item is the positive reference, we show that the reference bias and CIB act independently, both contributing strongly to the observed bias. Since the reference-independent CIB was similar in size to the one observed in all previous experiments, we conclude that the reference effect cannot account for the effect of choice.

Our generative modelling supports the conclusion that CIB is driven by at least two separate mechanisms: a conflict-driven, domain-general Consistency Bias (CB) and a domain-specific Value Update (VU).

CB is quite common in perceptual literature, being associated with a range of mechanisms, such as history effects [60,31] or decisional inertia [9]. In relation to preference-based choice, it can be compared to a conflict-driven dissonance reduction mechanism postulated by the dissonance reduction theory [27, 50,46]. In our specification, this mechanism is dependent only on the difficulty of the choice and does not affect underlying item evaluation.

VU mechanism is based on the proposal that our value inference process is conditioned on the memory of previous choices [28]. The idea is that our previous choices can serve as an indication of our preferences and the objective state of the world. Such choice driven inference has been implicated in many theoretical models [29,30]. We assume this mechanism can be described as a proportional update. Additionally, we model a memory decay process accounting for forgetting, so that choices made earlier in time can have a weaker effect on the current choice and judgment. In contrast to CB, this mechanism serves to improve one's estimation, hence it should exhibit domain-specificity and long-lasting effects. Unless there is an inherent correlation between dimensions, a cross-domain update would by definition be irrational.

In line with this theoretical distinction, we find that within-domain effects can be best explained as a conjunction of these two mechanisms, while cross-domain effects as driven solely by CB. Analysis of model parameters suggests

that negative updates are larger than positive ones (consistent with Experiment 4, as well as some findings from preference-based literature: [18,22]), and that the value-updates exhibit only a very marginal decay throughout the length of the task.

While VU has a clear adaptive interpretation, it is less clear why one should exhibit CB. One prominent theory suggests that CB might serve to facilitate action implementation [46]. Strikingly, a recent paper suggests that CB-driven evidence accumulation can sometimes enhance performance from purely computational perspective in both perceptual and higher-order inference tasks [12]. On a broader level, CIB is often considered as an instance of confirmation bias [11,61], which has been proposed to facilitate group cooperation and stability [48]. A different line of argumentation would claim that human brains are not well suited for solving task consisting of independent samples, which provide a constraint on our rational processing capacities [62,63]. Such an inductive bias might be a product of evolutionary adaptation to temporally-dependent environments, such as foraging patches [64].

We believe that further investigations on the nature of *within* and *cross*-domain CIB should focus on the areas of innovating the task-design space, expanding the modelling framework, and finding the neural correlates of the underlying cognitive processes.

Current task was designed to be a robust frame for comparing CIB between domains and choice-judgment congruencies. This comes at a cost of limiting the ability to test more specific cognitive mechanisms. Future studies should further explore the task design space employing dedicated task structures to tackle new hypotheses. Experiments 3 to 5 provide a sample of this approach.

Potential directions for future modelling involves a deeper exploration of how choices influence value uncertainties, accounting for spontaneous value drift, and incorporating a processes submodel of choice. Current model assumes that the value-update mechanism affects the central tendencies of value estimation, but it is also possible that choices reduce the uncertainty around the estimates. Using a Bayesian value update model (*e.g.* [65]), where both means and uncertainties fluctuate as a function of choices can lead to more accurate predictions and a better understanding of the cognitive process. The Kalman filter [66] has been previously used with success when modelling learning under uncertainty, when external values are inferred by the learner [67,68]. Similar approach could be applied to the learning of internal values. Spontaneous value drift refers to choice-independent fluctuations in item value in time. It is reasonable to assume that preference is more prone to time-dependent fluctuations than perception (one’s appetite for pizza might be different in the morning compared to the afternoon, but the judgment of it’s size will likely remain similar). Modelling this process can give bring novel insights into the nature of dynamic value estimation. Finally, incorporating decision times would allow for modelling the choices in an accumulation to bound framework [69], where item values drive the accumulation rate [70].

Future research should also focus on identifying a neural signature of both CB and VU mechanisms. Previous studies show preference value-updating in-

Table 1 Demographic information across experiments. *N* column contains the total number of participants, followed by the number of males within that sample (m). *Exc* column sums up all participants that were excluded, based on preregistered exclusion criteria. Columns 3 and 4 represent the mean and standard deviation of participants per experiment, respectively.

Exp	N	Exc	M _{age}	SD _{age}
1	23 (5m)	0	21.65	2.21
2	250 (155m)	14	26.35	8.20
3	50 (36m)	1	24.96	5.94
4	50 (34m)	1	24.67	7.04
5	50 (30m)	8	25.75	9.30

volves dorsal striatal [18] and hippocampal activity during reevaluation [19], suggesting choices affect both immediate value as well as modify memory representations; while choice conflict is tracked by anterior cingulate cortex and dorsolateral prefrontal cortex [18]. This distinction corresponds well with the idea of two separate mechanisms driving CIB. One promising way of approaching this problem is using multivariate voxel-pattern analysis (MVPA) for distinguishing shared and non-overlapping representations (*e.g.*, [71]) of CB and VU based adjustments driving the *within-domain* and *cross-domain* CIB.

Conclusion

We show that people can be influenced by their choices not only when the choices are relevant to the evaluation (*within-domain*), but also when they are not (*across-domains*). CIB is specific to voluntary choices, asymmetric, such that rejected items are undervalued more strongly than chosen items are overvalued, and independent of which item is considered the reference. The existence of *cross-domain* CIB and the mechanisms driving it can help us understand seemingly irrational, yet socially relevant behaviours such as changing political opinions based on voting or the emergence of polarized in-group worldviews, driven by one’s choices and actions.

While previous studies attempted to explain CIB with a single process, our generative modelling suggests that CIB is driven by two separate mechanisms: a conflict driven consistency bias contributing to any evaluation immediately following a choice, and a value-update, affecting only choice-congruent judgments. Both mechanisms have different temporal dynamics and functional interpretations. While value-updating is only beneficial when choice information is relevant to the evaluation, a general consistency bias can serve to reduce uncertainty, and facilitate action implementation.

Methods

Fig. 4 Task design and predicted effects. Panel a) represents the task structure, consisting of item ratings (repeated twice before the main task and once after) and the main task. Each trial of the task consisted of a choice followed by a judgment. Panel b) illustrates expected effects on of choice on the judgment phase. Columns represent judgment types; rows: choice types. Panel c) represents design adjustments in Experiments 3-5.

449 Participants

450 A total of 423 participants took part in five experiments (age range 18-70 years
 451 old, mean age 25.7 years, 163 females, 372 right-handed, Table 1). Experiment
 452 1 involved 23 participants recruited from Cardiff University School of Psychol-
 453 ogy participant panel for lab-based tasks. Experiments 2-5 involved 400 sub-
 454 jects from a participant recruitment portal *Prolific* (<https://prolific.co>).
 455 Consent was obtained from all participants. The study was approved by the
 456 Cardiff University School of Psychology Research Ethics Committee. Partici-
 457 pants in Experiment 1 were compensated with course credits. Participants in
 458 experiments 2-5 received cash payments for their participation.

Table 2 Design differences across experiments. Choice types refer to 2-alternative force choice. judgments refer to estimation of difference between item values on a continuous scale from -100 to 100. *Stay* judgment factor refers to which item out of a unique pair was replaced (and which stayed) during the judgment. *Ref* refers to which item was considered the referenced item out of each unique pair. Unique pair column specifies how often (and in which conditions) was a unique pair of two items repeated.

Exp	Choice Types	Judgment Types	Trials	Unique Pair Reps
1	Pref Size No	Dom. (Pref, Size)	906	6 times (1 x cond)
2	Pref Size No	Dom. (Pref, Size)	198	3 times (1 x choice type)
3	Pref Size Forced	Dom. (Pref, Size)	264	4 times (1 x choice type)
4	Pref Size No	Dom. (Pref, Size) x Stay (Item1, Item2)	264	4 times (1 x judg. type)
5	Pref Size No	Dom. (Pref, Size) x Ref. (Item1, Item2)	264	4 times (1 x judg. type)

Power analyses, exclusion criteria, experiment procedures and further analysis plans were preregistered for Experiments 2-5 (see: *Online Resources*). For Experiment 2, a sample size of $N=250$ provides 80% power to detect a moderate effect of correlations between behavioral performance and trait measures (Pearson's $R=0.2$, $\alpha = 0.01$, [72]). The sample size for each of the Experiments 3-5 ($N=50$) were informed by the smallest effect size in Experiment 2 ($d=0.7$ in the incongruent perceptual condition), which provides over 95% power to detect the bias effect at $\alpha = 0.05$. Details, together with precise exclusion criteria can be found in *Online Resources*.

Stimuli

All five experiments used food pictures from the *Food-Pics* database [73]. 18 food pictures were selected for Experiment 1, and a separate set of 24 for Experiments 2-5 (see: *Supplementary Materials*). The use of two stimulus sets ensures that our results are generalizable and not dependent on specific food pictures. The food items were chosen to be diverse and equally represent different categories. In Experiment 1, these categories contained: sweet snacks, savory dishes, and healthy foods. In Experiments 2-5 healthy foods were split into fruits and vegetables making up a total of 4 categories. Each item was presented on a squared white background (350×350 pixels). The size of each stimulus was defined as the proportion of the area taken by the actual food picture (*i.e.*, non-white pixels). Each food category contained two relatively small ($<35\%$ of non-white pixels), two medium ($36-45\%$ of non-white pixels) and two relatively large items ($>46\%$ of non-white pixels).

During the choice and judgment phase, two items were presented on the opposite sides of the screen with a symbol indicating *response type* (choice or judgment) placed centrally above the items; *domain* (size, preference, no-choice or forced choice) centrally in the gap between the items and a scale below

(judgments only). The judgment scales were horizontal and had the width spanning the width of the 2 items (Experiments 1-4) or vertical (Experiment 5; Figure 4) Only two ends and the middle of the scales had markers. No labels were present.

Procedure

All experiments followed a procedure consisting of three main stages (Figure 4). In the first and third stages, participants rated their preference and the size of each stimulus. The second stage was the main task, where on each trial participants made a choice between two items, followed by a comparative judgment of the items on a continuous scale. Choice and judgment conditions varied across experiments (see Table 2). In Experiment 1, participants completed two behavioral sessions conducted on different days, each session taking between 75 and 90 minutes. All online experiments were approximately of similar length, taking participants between 45-75 minutes to complete. Experiment 1 was written and conducted in *PsychoPy* v3.1.2 [74]. Online experiments were written and conducted in *jpsych* v6.0.5 [75].

Stage 1: Initial rating. Participants performed initial preference and size-based ratings of 18 (Experiment 1) or 24 (Experiments 2-5) food items on a continuous scale from 1 to 100. For preference-based ratings, participants rated item desirability from strong dislike (1) to strong liking (100). In the perceptual-based rating, participants rated the size of each food picture with respect to the white background, in terms of the proportion of non-white pixels. Each participant completed a total of 72 (Experiment 1) or 96 (Experiments 2-5) rating trials, with two iterations of both types of ratings. Rating type order was counterbalanced across participants and item order was randomized within each rating. For Experiment 1, all 18 items were used in the main task. For Experiments 2-5, the top 12 items on the preference scale were used in the main task.

On each rating trial, a food stimulus was presented in the center of the screen. A task cue (red heart for preference or a blue circle with outward arrows for size; see Figure 4) was presented on top of the stimulus to indicate the type of rating. A white rating scale was presented below the food stimulus with markers placed on both ends. A small circle on the rating scale indicates the current rating, with its default position in the middle of the scale. Participants used *z* and *m* keys to move the value indicator to the left or right (Experiment 1) or used a mouse to drag or click on the scale (Experiments 2-5). There was no time limit for response.

Stage 2: Main Task. Participants performed different versions of the main task with small changes in experimental design to address specific research questions (see Table 2). Each trial consisted of a choice between 2 items followed by a judgment of difference between item values on a continuous scale from -100 to 100. Experiments 1 and 2 consisted of three types of choices (preference, size, or no-choice) and two types of judgments (preference or

size). No-choice condition required participants to withhold a response while observing the items on screen. In Experiment 3, no-choice condition was replaced with forced choice, where participants were required to choose one of the items indicated by the experimenter (*i.e.*, the item with a highlighted border). In Experiment 4, one of the items was randomly replaced after the choice and before judgment. In Experiment 5, during the judgment phase, one of the items was marked as reference and the judgment task was reframed to evaluate whether the reference item is larger/more valuable, compared to the non-reference item, so that positive evidence always favored the reference item.

Task was divided into 51 (Experiment 1) or 66 (Experiments 2-5) trial blocks. Participants took short self-paced breaks between blocks. Participants had a time limit of 2250 ms (Experiment 1) or 4000 ms (Experiments 2-5) to choose and 6000 ms (Experiment 1) or 5500 ms (Experiments 2-5) to make a judgment. Similar to the rating phase, participants used either z and m keys (Experiment 1) or mouse clicks (Experiments 2-5) to choose and move left and right along the scale. A choice was indicated with a green border surrounding the chosen item for the length of the choice phase. In Experiment 1, the choice screen remained visible for the full length (2250 ms), irrespective of reaction time speed, followed immediately with a judgment screen. In Experiments 2-5, the choice screen disappeared 500 ms after making a choice. The trial was completed after confirming the judgment with pressing the space bar (Experiment 1) or clicking the “confirm” button (Experiments 2-5). If no response was provided in time, a prompt saying “Too slow” was presented for 500 ms, after which the next trial was presented.

Stage 3: Final rating. After completing Stage 2, participants performed the preference and perceptual-based ratings for the third time (18 items in Experiment 1 and 24 items in Experiments 2-5).

Questionnaires (Experiment 2). In Experiment 2, after the final rating stage, participants filled five questionnaires measuring Preference for Consistency [76], Extraversion (BFI-2-S,[77]), Susceptibility to Confirmation Bias (CI,[78]), Positive and Negative Affect (I-PANAS-SF; [79]) and Action Control (ACS-90; [80]). Questionnaire order was randomized across participants. Results of the relation between questionnaire scores and task measures can be found in the *Supplementary Materials*.

Data processing

No-response trials were removed (Experiment 1: 2.5%; Experiment 2: 2.8%, Experiment 3: 1.9 %; Experiment 4: 3.5%; Experiment 5: 3.8%). For modelling, we removed participants whose final ratings were not saved due to a saving error (Experiment 2: 6 cases, Experiment 5: 1 case).

Right-side judgment bias (RB) was defined as a difference between the judgment J and the difference between right and left item values in choice domain d on trial t :

$$RB_t = J_t - (\bar{I}_{d,right} - \bar{I}_{d,left}) \quad (1)$$

where $\bar{I}_{d,right}$ and $\bar{I}_{d,left}$ are the means of initial ratings for the right and left item respectively. Similarly, choice-induced bias (CB) was calculated by conditioning the sign on the choice:

$$CB_t = \begin{cases} J_t - (\bar{I}_{d,right} - \bar{I}_{d,left}) & \text{if } choice_t = right \\ -(J_t - (\bar{I}_{d,right} - \bar{I}_{d,left})) & \text{if } choice_t = left \end{cases} \quad (2)$$

Behavioral Modelling

For all experiments, we report the results from Bayesian Mixed-Effects models using standard priors from the *brms* R package [81]. Random effects structure includes intercepts and slopes for all regressors of interest (exact model specification can be found in *Supplementary Materials*). We report posterior distribution medians (*med*), 95% posterior credible intervals (CI), probability of directionality (pd; % of posterior density larger or smaller than 0), and, where the result is found to be significant, % of posterior in the Region of Practical Equivalence (ROPE) [82]. Analogous to frequentist analysis, we define significance as $pd > 0.95$. ROPE can be interpreted as an arbitrary null region where effect size is small enough not to be meaningful [83]. We set the ROPE range to $[-2, 2]$ ($\pm 1\%$ of the scale), as finer differences would be difficult for participants to distinguish. Frequentist analyses can be found in the *Supplementary Materials*.

Computational Modelling

Our model aims at explaining peoples' choices and judgments by estimating the internal values associated with item preference and size from which the data is generated, and how they change in time. The model assumes that values fluctuate as a function of choice, so that choosing or rejecting an item updates its estimation by a fraction of its value (proportional update). An item value at any point is not allowed to exceed the boundaries of the scale (0-100). The starting preference and size values of each item are derived from the mean of the two initial ratings on the appropriate scales. We model 4 distinct phases on each trial: *choice*, *value update*, *judgment*, and *value attenuation*.

Choice. The choice between 2 items is modelled using the *softmax* function, which converts item values into choice probabilities:

$$p(A) = \frac{e^{\tau V_{d,t}(A)}}{e^{\tau V_{d,t}(A)} + e^{\tau V_{d,t}(B)}} \quad (3)$$

where $V_{c,t}(A)$ and $V_{c,t}(B)$ represent value estimates for items A and B in a given domain c (preference or size) on trial t , and τ represents inverse temperature, which is often interpreted as the noisiness of choice.

Update. After each choice, both chosen I_{ch} and rejected I_{rej} item values are updated:

$$V_{d,t+1}(I_{ch}) = V_{d,t}(I_{ch}) + \alpha V_{d,t}(I_{ch}) \quad (4)$$

$$V_{d,t+1}(I_{rej}) = V_{d,t}(I_{rej}) + \beta V_{d,t}(I_{rej}) \quad (5)$$

where α and β represent proportional updates for the chosen and rejected items respectively. Both update parameters can take values between -1 and 1. α and β can vary dependent on choice domain (size, preference) and congruency (whether choice-congruent or choice-incongruent domain is updated). Together, this gives a maximum 8 update parameters.

Judgment. Judgment is assumed to follow a normal distribution, centered at the difference of the true subjective value between the right and left items:

$$J_t \sim N(V_{r,d,t+1} - V_{l,d,t+1} + CB_i, \sigma_i) \quad (6)$$

where $V_{r,d,t+1}$ and $V_{l,d,t+1}$ represent the current (updated) values of the right and left items in domain d on trial t , and σ_i represents individual-level variability. The CB parameter represents a consistency-driven bias term that does not affect the underlying value estimations. CB_i is moderated by conflict, and it's valence is dependent on choice, so that it takes positive values if right item was chosen, negative values if left was chosen, and 0 when no choice was made:

$$CB_i = \begin{cases} \gamma_i * c_{d,t} & \text{if } choice_t = right \\ -(\gamma_i * c_{d,t}) & \text{if } choice_t = left \\ 0 & \text{if } choice_t = none \end{cases} \quad (7)$$

where γ_i represents the consistency-bias parameter, and $c_{d,t}$ is the normalized conflict in the domain of choice on given trial, calculated as the absolute difference in item values.

Attenuation. Finally, item values are attenuated towards their initial estimates:

$$V_{d,t+1}(A) = V_{d,t+1}(A) - k(V_{d,t+1}(A) - V_{d,init}(A)) \quad (8)$$

$$V_{d,t+1}(B) = V_{d,t+1}(B) - k(V_{d,t+1}(B) - V_{d,init}(B)) \quad (9)$$

where k is the discounting parameter and can take values between 0 and 1. A k of 1 indicates perfect discounting, and the model is reduced to a fixed-value model where values are never updated. A k of 0 indicates no discounting (permanent update). Values of k in-between suggest a decay effect, where choices made longer in the past have less influence on current value. This accounts for the possibility that choice-driven value updates might be temporary and decay when earlier choices get forgotten.

Model fitting procedure

We fitted the model using Bayesian Hierarchical Modelling, estimating group level and subject-level parameters. For fitting purposes, the judgment values were divided by 100, constraining the possible range between $[-1,1]$. Following previous work in this domain [84,85] we used uniform priors on a realistic constrained range:

$$\alpha \sim U(0.0, 0.5) \quad (10)$$

$$\beta \sim U(0.0, 0.5) \quad (11)$$

$$\gamma \sim U(0.0, 0.5) \quad (12)$$

$$\tau \sim U(0, 10) \quad (13)$$

$$\sigma \sim U(0, 1) \quad (14)$$

$$k \sim U(0, 1) \quad (15)$$

We used *Stan* programming language [86] for the hierarchical implementation of our model. For each model, we generated 2 independent chains of 2000 samples from the joint posterior distributions of the model parameters, using Hamiltonian Monte Carlo (HMC) sampling [86]. The initial 1000 samples were discarded as burn-in. To assess model convergence of the chains we calculated the Gelman-Rubin convergence diagnostic $\hat{R}$ for each model parameter. Similar to previous work [87,55] we used $\hat{R} < 1.1$ as a criterion for good convergence.

Model comparison

We compare 4 theoretically-driven models fitted to data from Experiment 2. *Null* model fixes all updating parameters to 0 and k to 1, resulting in no value updating or consistency bias. *Consistency-Only* model assumes only a general consistency bias and no value-updating. Congruent Update model assumes only choice-congruent values are updated. *Update-Only* model assumes all choices induce a value update, but no consistency bias. Full Update model allows all update parameters to vary, together with a general consistency bias. Direct model fit was measured using Leave-One-Out (LOO) information criterion [43]. LOO evaluates the model fit while controlling for model complexity, with lower value indicating better out-of-sample prediction. We use LOO scores to determine model stacking weights, which give the predictive probability of each model being best [44]. When comparing 2 models, a probability of .9 or larger in favour of one of them is considered decisive [85]; otherwise a simpler model is preferred.

Model evaluation

To evaluate the winning model in terms of prediction accuracy we 1) generate posterior predictive distribution and correlate model predictions with participant choices across subjects, and 2) regress the updated item values onto final rating values and compare whether the model-derived values can predict final ratings better than the initial ratings.

To check whether the model is capable of reproducing parameter values within the plausible range, we perform parameter recovery tests for update parameters after model fitting [85]. We 1) draw a set of group-level parameters from joint posterior group-level distribution, 2) simulate 200 participants, whose individual-level parameters are drawn from the group-level sample 3) fit the simulated data using the winning model, 4) compare the simulated and recovered parameter values at both levels (Supplementary Materials).

Online Resources

Preregistrations and all other online resources can be found on the project's *OSF* page <https://osf.io/p8ukb>.

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