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Using Computational Models to Understand the Role and Nature of Valuation Bias in Mixed Gambles

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Abstract

It is a well-known observation that people tend to dislike risky situations that could potentially lead to a loss, a phenomenon that is called loss aversion. This is often explained using valuation bias, i.e., the subjective value of losses is larger than the subjective value of gains of equal magnitude. However, recent work using the drift-diffusion model has shown that a pre-valuation bias towards rejection is also a primary determinant of loss-averse behavior. It has large contributions to model fits, predicts a key relationship between rejection rates and response times, and explains the most individual heterogeneity in the rejection rates of participants. We analyzed data from three previously published experiments using the drift-diffusion model and found that these findings generalize to them. However, we found that valuation bias plays the most important role in predicting how likely a person is to accept a given gamble. Our findings also showed that a person's loss aversion parameter, λ, which captures their propensity to avoid losses is closely related to valuation bias. These results combined highlight the importance of valuation bias in understanding people's choice patterns. Finally, using the leaky, competing accumulator model, we show strong mimicking between valuation bias and an attentional bias wherein people pay more attention to losses as compared to gains. This finding suggests that behaviors that seem to arise due to valuation bias may arise due to such an attentional bias. Our code is available at: `https://github.com/nishadsinghi/valuation-bias-ddm`

Keywords: loss aversion, decisions under risk, valuation bias, drift-diffusion model, attentional bias

Introduction

Suppose you are presented with the following gamble: an unbiased coin is flipped. You earn \$11 if it lands heads but lose \$10 otherwise. Would you play this gamble? Numerous studies have shown that people dislike such gambles, even when it is statistically advantageous to accept them (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). This suggests that people dislike risky situations which could potentially lead to a loss, or in other words, people are *loss averse*.

Kahneman and Tversky (1979) initially coined the term loss aversion. In the framework of their prospect theory, loss aversion arises due to a *valuation bias*, i.e., the subjective value of losses is larger than the subjective value of gains of equal magnitude. Mathematically, the subjective utility of a gain of x is equal to x, whereas the subjective utility of a loss of x is equal to λx, with $\lambda > 1$. In the case of gambles with an equal probability of resulting in a gain or a loss (gambles that can result in both gain or loss are referred to as *mixed gambles*), the utility is $U = 0.5 \cdot G - 0.5 \cdot \lambda \cdot L$, where G is the potential gain, L is the potential loss, and λ is the prospect theory loss aversion parameter, which captures how people weigh losses relative to gains (the larger the value of λ, the more loss averse someone is). A person's degree of loss aversion, λ, is often estimated using logistic regression, with $A_i = \sigma(\beta_G G_i - \beta_L L_i + \alpha)$ and $\lambda = \beta_L / \beta_G$, where β_G and β_L are the regression coefficients for the gain G_i and loss L_i in gamble i, A_i is the decision (1: accept, 0: reject), and $\sigma(x) = (1 + e^{-x})^{-1}$. α is a constant term known as *fixed utility bias*, which captures a person's bias towards acceptance ($\alpha > 0$) or rejection ($\alpha < 0$) regardless of the gain and loss.

The valuation bias formulation is widely influential and the predominant explanation for loss aversion. However, some studies have challenged this view and have proposed other explanations for loss aversion (See Gal and Rucker (2018) for a review). One such mechanism which can lead to loss aversion is the *status quo bias* (Gal, 2006; Gal & Rucker, 2018). According to this, people have a tendency to maintain the status quo, and they reject the gamble because accepting it would change the status quo. This reflects a prior bias toward rejecting gambles (i.e., a *pre-valuation bias*) even before the gamble is presented. Since pre-valuation bias comes into play before the agent has any knowledge of the gamble, it acts in the same way on all gambles. It is important to note that while both pre-valuation bias and fixed-utility bias are independent of the specific gamble, they differ in some ways. In particular, fixed-utility bias affects the utility of a gamble (although this effect is the same on all gambles) whereas pre-valuation bias is unrelated to utility. Further, pre-valuation bias acts before the decision-maker starts to evaluate the gamble, whereas fixed-utility bias affects the process of evaluating the gamble and deciding which action to choose.

Recently, Zhao, Walasek, and Bhatia (2020) employed the computational framework of the drift-diffusion model (Ratcliff, 1978) to understand the psychological mechanisms that give rise to loss aversion, and found that pre-valuation bias is a primary determinant of loss aversion. In particular, they found that pre-valuation bias has a distinct behavioural signature expressed in the relationship between participants' choices and response times (RTs), which was also observed in empirical data. Pre-valuation bias also captured the most individual heterogeneity in the rejection rates of participants.

In this study, we seek to build on the work of Zhao et al. (2020) and better understand the psychological mechanisms underlying loss aversion using the drift-diffusion model. In particular, we argue that a primary goal of economists is to predict how people would react to a given gamble (i.e., people's choices), and it is not clear how people's choices are affected by the psychological mechanisms discussed so far. Since pre-valuation bias is independent of the specific gamble, it may not be sufficient to capture fine-grained information about which particular gambles a person likes, and valuation bias may be necessary to do so. We empirically tested this hypothesis in two ways. Using the drift-diffusion model, we analyzed data from three previously published studies (including Zhao et al. (2020)) and found that models without valuation bias were not able to properly predict people's probability to accept a given gamble. Further, we found that the loss aversion parameter, λ, estimated via logistic regression has the strongest correlation with valuation bias. These results combined highlight the importance of valuation bias in predicting people's choice patterns.

We also used computational modeling to better understand the nature of valuation bias. Using eye-tracking, Sheng et al. (2020) showed that people with a higher degree of valuation bias spend more time looking at the loss value as compared to the gain value of a gamble. This suggests an *attentional bias*, wherein agents pay more attention to losses as compared to gains during the decision-making process. Using the framework of the leaky, competing, accumulator model (Usher & McClelland, 2001, 2004), we found that valuation bias and attentional bias are empirically indistinguishable from each other, which hints that behaviors appearing to arise due to valuation bias may arise due to attentional mechanisms.

Computational Models

As previously discussed, several theories have been proposed to explain loss aversion in mixed gambles (see Gal & Rucker, 2018 for a review), and it can be hard to tease them apart, as they often make qualitatively similar predictions. Computational models allow us to quantify their predictions and perform ablative analyses to isolate their contribution to behaviour. However, traditional economic models like prospect theory are not sufficient for this purpose, as they cannot account for mechanisms that do not depend on the utility of a gamble but may still influence the decision, such as pre-valuation bias. Additionally, these models do not incorporate response times, which can provide important insight into the decision-making process (Konovalov & Krajbich, 2019).

One family of models that can help overcome these limitations is of evidence accumulation models. Models from this family, such as the drift-diffusion model and the leaky, competing accumulator have successfully explained data from a wide range of perceptual and value-based decision-making tasks (Gold & Shadlen, 2007). These models can also capture people's prior bias toward the rejection of gambles as well as predict their response times.

Drift-Diffusion Model

The drift-diffusion model (DDM) assumes that the decision-maker starts from a starting point γ and deliberates over time in a stochastic manner, accumulating information about its preferences over time. The rate of accumulation is controlled by the *drift-rate* (ν) which depends on the utility of the gamble as $\nu_i = \beta_G G_i - \beta_L L_i + \alpha$. The decision is made when the accumulated evidence reaches one of the two thresholds (the gamble is accepted if it reaches $+\theta$ and rejected if it reaches $-\theta$). Response time is the sum of the time taken to reach the threshold and a non-decision time (denoted by τ) which embodies the time taken by processes such as perception and motor execution. This process is illustrated in Fig. 1.

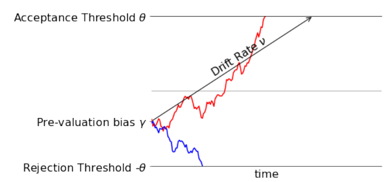

Figure 1: The evidence accumulation process in DDM. The red and blue solid lines show how two independent trials unfold over time beginning from the starting point γ and ending at the two thresholds, $+\theta$ and $-\theta$ respectively. The arrow represents the expected trajectory without the effect of noise. The slope of this arrow is equal to the drift rate.

In this model, pre-valuation bias is captured by the starting point γ. In particular, if $\gamma < 0$, less evidence is required to reach the lower threshold, making it easier to reach it and subsequently reject the gamble, even in the absence of valuation bias. Valuation bias, which captures that losses may have higher subjective utility, is given by the ratio $\lambda_{DDM} = \beta_L/\beta_G$. Further, fixed-utility bias, which captures how subjective utility is biased towards rejection irrespective of the gain and loss values, is given by α.

Leaky, Competing Accumulator

The leaky, competing, accumulator (LCA) is a biologically inspired model of decision-making belonging to the class of accumulator models of choice (Usher & McClelland, 2001, 2004). In the context of mixed gambles, it consists of two accumulators, A1 and A2, corresponding to accepting and rejecting the gamble, respectively. At every time t, the attentional switching mechanism randomly selects whether to pay attention to gain or loss (see Usher and McClelland (2004)). Then, the subjective value of the gain or the loss selected in the previous step is fed to A1, while A2 receives an input of 0 (because the gain/loss associated with rejecting the gamble is 0). In addition, both accumulators receive fixed inputs $I_{0,1}$ and $I_{0,2}$ respectively, that do not depend on the selection made by the switching mechanism. The accumulators compete against each other, and the first one to reach its threshold wins. This process is illustrated in Fig. 2.

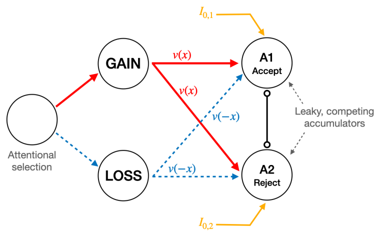

Figure 2: Schematic of the LCA. Accumulators A1 & A2 correspond to the two options - accept and reject gamble. At any instant, the attentional selection mechanism attends to one of the attributes defining the gamble (gain or loss). The red and blue arrows show the information flow when the selection mechanism is attending to gains and losses respectively.

In this model, pre-valuation bias is reflected in the starting points of A1 and A2. Concretely, if A2 has a larger starting point than A1, less evidence is required for it to reach the threshold, making rejection the more likely choice. Valuation bias is captured by the subjective value function $v(x) = x, x \geq 0$ and $v(x) = \lambda x, x < 0$ with $\lambda > 1$. A fixed utility bias towards rejection can be induced by having $I_{0,2} > I_{0,1}$. In addition to these mechanisms, LCA can account for the decision-maker paying more attention to losses as compared to gains during the deliberation process. In the unbiased case, the switching mechanism selects gain or loss with equal probability. However, in the biased case, it could select loss with a higher probability, increasing its influence over the decision.

Methods

Experiments

Dataset-1 The first experiment we analyzed is Experiment 1 of Zhao et al. (2020). Participants ($n = 49$) had to play a series of 200 mixed gambles. Each gamble could result in either a gain or a loss with equal probability. The values of gain and loss were selected from the set {10, 20, 30, 40, 50, 60, 70, 80, 90, 100}. These values were converted to USD by multiplying them with 0.1. Participants were informed that at the end of the experiment, one of the gambles would be selected randomly and if they had accepted that gamble, it would be played out in front of them by the experimenter. The result of this gamble would decide their bonus payment on top of a fixed show-up fee.

Dataset-2 The second experiment we analyzed is Study 1 (non-adaptive) of Konovalov and Krajbich (2019). Participants ($n = 39$) had to complete a series of trials, each of which consisted of a choice between a sure non-negative amount and an equiprobable mixed gamble. The total number of trials per participant was 276, and in 224 of these trials, the value of the sure option was \$0. To maintain similarity with dataset-1, we analyzed only these 224 trials.

Dataset-3 The third experiment we analyzed is from Sheng et al. (2020). Participants ($n = 94$) had to play a series of 200 equiprobable gambles, in which the values of gain and loss were chosen from the set USD $\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$. Participants were told that at the end of the experiment, one gamble would be randomly selected, and their final payoff would be determined by their response in the selected gamble.

Model Fitting

Following the approach of Zhao et al. (2020), we used the HDDM (Wiecki, Sofer, & Frank, 2013) package to fit DDM on the three datasets with the free parameters being β_G, β_L, α, and γ. This package allows for hierarchical Bayesian estimation of individual and group-level parameters using MCMC (Gamerman & Lopes, 2006), with group-level parameters forming the prior for individual parameters. We first used the library's in-built function to find a good starting point for the sampling process, followed by running 4 separate chains of 5,000 samples each, the first 1,000 samples of which were discarded as burn-in. The $\hat{R}$ of all parameters was less than 1.1, suggesting convergence (Gelman, Rubin, et al., 1992).

LCA model was fit to the datasets using the Metropolis algorithm (Usher & McClelland, 2001). The goodness of fit was approximated by comparing model simulations with experimental data using a χ^2 cost function:

$$\chi^2 = \sum_{\mathcal{G}} \sum_{i} \frac{N(p_i - \pi_i)^2}{\pi_i} \tag{1}$$

where $\mathcal{G}$ is the set of all gambles, p_i is the proportion of RTs generated by the model and π_i is the proportion of experimental RTs that lie in the i^{th} bin, and N is the number of observations for the given value of loss and gain. The boundaries of the bins correspond to the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles of the empirical data, computed separately for accept and reject RTs (i.e., 12 bins, 6 for each response).

Results

DDM Group-Level Parameters

In this section, we present the parameter estimates obtained by fitting DDM onto the three datasets, following the approach of Zhao et al. (2020). The posterior mean (group level distribution) of the valuation bias parameter, λ, was 1.49 in dataset-1, 1.44 in dataset-2, and 1.57 in dataset-3. The 95% credible interval for β_L was strictly greater than the interval for β_G in all datasets, implying that the utility function is steeper for losses than gains. Average value of λ across all participants was 1.88 in dataset-1, 1.51 in dataset-2, and 1.82 in dataset-3. The number of participants with $\beta_L > \beta_G$ was 40 (81.6%), 32 (82%), and 84 (89.3%) for the datasets respectively. These results suggest that participants in all three experiments showed a valuation bias towards rejection.

The posterior mean (group-level) of the pre-valuation bias parameter, γ, was -0.214 in dataset-1, -0.135 in dataset-2, and -0.075 in dataset-3. 37 (75.5%) participants in dataset-1, 28 (71.8%) participants in dataset-2, and 68 (72.3%) participants in dataset-3 had $\gamma < 0$. The number of participants with a strictly negative 95% confidence interval of γ was 33 (67.3%), 23 (58.9%), and 35 (37.2%) in the three datasets respectively. These findings suggest that participants in all three experiments had a pre-valuation bias toward rejecting gambles.

In summary, these results indicate the presence of both valuation bias and pre-valuation bias toward rejection in the three experiments.

Behavioural Marker for Pre-valuation Bias

In addition to parameter estimates, Zhao et al. (2020) predicted a behavioral marker for pre-valuation bias. Concretely, pre-valuation bias has a larger impact on faster trials because its effect diminishes as the decision process unfolds. Hence, a starting bias towards rejection would predict more rejections in faster trials as compared to slower trials after controlling for the effect of different drift rates. To test if this behavioural marker was present in experimental data, we plotted acceptance rates vs. response times adjusted for different drift-rates (referred to as choice-RT plots, see Zhao et al. (2020) for more details). We found this marker was present in all three datasets, as shown in Fig. 3, which indicates the presence of a pre-valuation bias towards rejection in participants.

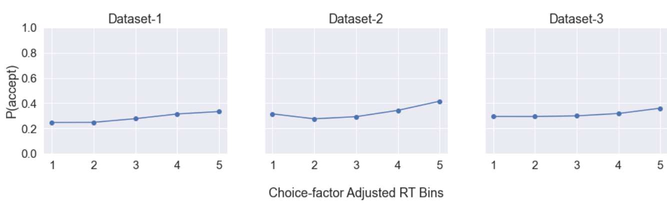

Figure 3: Acceptance rate vs. choice-factor adjusted (for gain and loss value of gamble) RT bins of experimental data. Response times increase from left to right. Acceptance rates increase with choice-factor adjusted RTs, indicating the presence of a pre-valuation bias towards rejection.

Following Zhao et al. (2020), we constructed three restricted DDM models (1) no valuation bias (setting $\beta_G = \beta_L$), (2) no pre-valuation bias (setting $\gamma = 0$), (3) no fixed-utility bias (setting $\alpha = 0$) and compared them against experimental data in terms of this behavioral marker (i.e., choice-RT relationship). We found that the model without pre-valuation bias is the worst at capturing the choice-RT relationship, further highlighting the importance of this mechanism in capturing this behavioral marker (Table 1). These results combined provide further evidence for the presence of a pre-valuation bias in people toward the rejection of gambles.

Capturing Choice Patterns

While Zhao et al. (2020)'s finding that pre-valuation bias is necessary to capture choice-RT relationship holds up across all three experiments, we remark that valuation bias may affect behavior in a distinct way. In particular, we focus on a person's probability to accept a given gamble. Intuitively, this can be broken down into two components. The first component is the overall tendency to accept or reject gambles. The second component pertains to how their responses change as a function of the gain and loss. For instance, person A and person B both might have an acceptance rate of 50% when presented with an equiprobable gamble with possible outcomes +10 and -10. However, their acceptance rates might change to 20% and 45% respectively for the gamble with outcomes +10 and -12, in which case we would say that person A is more sensitive to the ratio of gain and loss in the gamble. Since pre-valuation bias is independent of the specific gamble, it is plausible that it would be able to capture a person's overall tendency to accept or reject gambles. However, pre-valuation bias may not be sufficient to capture fine-grained information about which particular gambles a person likes, and valuation bias may be necessary to do so.

Table 1: Mean Absolute Error (MAE) values of choice-RT (adjusted for choice factor) patterns for full and constrained DDM models. Smaller is better.

	Full Model	$\beta_G = \beta_L$	$\gamma = 0$	$\alpha = 0$
Dataset-1	0.023	0.019	0.034	0.020
Dataset-2	0.020	0.019	0.041	0.018
Dataset-3	0.019	0.015	0.029	0.022

To test this, we compared the rejection rates predicted by the full and constrained DDM models against those of humans and found that the model without valuation bias has the worst fits, both visually and as indicated by R^2 values (Fig. 4; Table 2). This confirms our prediction that valuation bias is necessary in order to properly capture choice patterns.

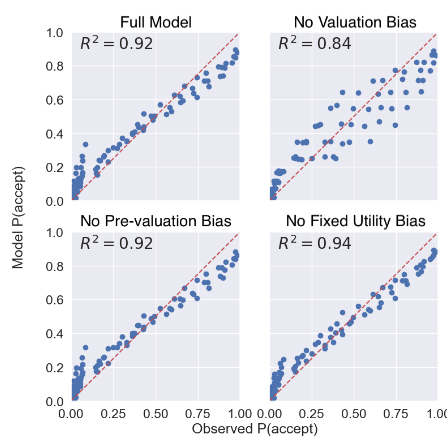

Figure 4: Probability-Probability plots for empirical acceptance rates (x-axis) and DDM predicted acceptance rates (y-axis), where each point corresponds to a combination of gain and loss displayed to the participants (dataset-3 only). Similar trends were observed for datasets 1 and 2.

Individual Heterogeneity

Zhao et al. (2020) found that among all parameters of DDM, γ had the strongest correlation with participants' rejection rates.

Table 2: R^2 values for acceptance rates as a function of gamble values. Larger is better.

	Full Model	$\beta_G = \beta_L$	$\gamma = 0$	$\alpha = 0$
Dataset-1	0.87	0.79	0.84	0.88
Dataset-2	0.65	0.50	0.62	0.69
Dataset-3	0.92	0.84	0.92	0.94

This led them to speculate that λ computed using logistic regression over choice data (referred to as λ_{LR} for clarity) might have a stronger relationship with pre-valuation bias as compared to valuation bias. In our analyses, we found that γ indeed shows a high correlation with rejection rates across all three datasets (Table 3). However, we argue that this does not necessarily imply that it also has the strongest relationship with λ_{LR}. Since λ_{LR} is estimated from the ratio of the regression coefficients of gains and losses, we argue that it should capture information about a person's sensitivity to the particular gamble. Due to this, we suspected that λ_{LR} might be more closely linked to valuation bias than to pre-valuation bias. To test this, we computed the correlations between λ_{LR} and the parameters of the DDM across all experiments. We found that λ_{LR} had the strongest correlation with λ_{DDM} in two experiments (Table 4), providing support to our hypothesis. Further, we performed standardized multiple regression of λ_{LR} on the three parameters of the DDM and found that λ_{DDM} had the largest regression coefficient in datasets 2 and 3 (Table 5). These results about the relationship between λ_{LR} estimated from choice data and valuation bias further highlight the role of valuation bias in understanding choice patterns.

Table 3: Pearson correlation between acceptance rates of participants and DDM parameters (* = $p < 0.01$).

	λ	γ	α
Dataset-1	-0.13	0.88*	0.45*
Dataset-2	0.16	0.81*	0.89*
Dataset-3	-0.33*	0.65*	0.54*

Table 4: Pearson correlation between logistic regression λ_{LR} of participants and DDM parameters (* = $p < 0.01$).

	λ	γ	α
Dataset-1	0.22	-0.34	0.07
Dataset-2	0.66*	-0.30	-0.26
Dataset-3	0.86*	-0.44*	0.18

Model Mimicking

We investigated how similar two mechanisms are to each other by looking at how well they can mimic each other. Following Ratcliff and Smith (2004), we assessed mimicking between mechanisms in two ways. First, we fit two models to the behavioral data, with each model instantiating one of the mechanisms we wanted to compare. If both models fit experimental data equally well, we could say that the two mechanisms mimic each other from an empirical standpoint. Second, we say that two models mimic each other if synthetic data generated by one could be captured well by the other. The parameters used to generate this synthetic data were obtained by fitting the model to experimental data (separately for each of the three datasets). We note that approximating the goodness of fit of an LCA model using χ^2 values can be noisy as it relies on generating stochastic simulations from the model. This implies that two different sets of simulations generated from the same model with identical parameters might have a positive χ^2 value. To account for this, we included a baseline wherein we computed the χ^2 value of another set of simulations obtained from the generating model with exactly identical parameter values to estimate the best-case value of χ^2. Please note that we always compare the χ^2 values of models with equal number of free parameters.

Table 5: Standardized regressions of logistic regression λ_{LR} on λ_{DDM}, γ and α (parentheses contain standard error values for the regression coefficients).

	λ	γ	α
Dataset-1	0.27 (0.534)	-1.14 (0.494)	0.42 (0.550)
Dataset-2	0.91 (0.091)	-0.21 (0.103)	-0.49 (0.109)
Dataset-3	1.94 (0.119)	0.17 (0.105)	-0.59 (0.104)

Relationship between Valuation Bias and Attentional Bias

In addition to valuation bias, pre-valuation bias, and fixed-utility bias, we consider another mechanism that can cause high rejection rates in mixed gambles. Various studies have shown that negative information draws more attention than positive information (Anderson, Siegel, Bliss-Moreau, & Barrett, 2011; Dijksterhuis & Aarts, 2003; Pratto & John, 1991). It has also been shown that attending to a particular attribute increases its weight in the decision process, which can bias responses (Fisher, 2017; Krajbich, Armel, & Rangel, 2010). Hence, it is possible that the bias toward rejection of gambles arises because decision-makers attend to losses more than gains during the decision-making process.

The switching mechanism of LCA allows us to investigate the effects of attending to losses more than gains and compare it with the three mechanisms discussed so far. We did so by assessing how well an LCA model with attentional bias can mimic LCA models with these biasing mechanisms. First, we fitted four LCA models, each having only one biasing mechanism, and found that models with attentional bias and valuation bias have similar χ^2 values across all three experiments (Fig. 5). Next, we analyzed how well synthetic data generated using a model with valuation bias can be fitted by a model with attentional bias, and vice-versa. We found that both models are able to capture data generated by the other quite well (Figures 6 & 7). These findings indicate that from an empirical standpoint, LCA models with attentional bias and valuation bias behave in a similar way, hinting towards a potential link between the two mechanisms.

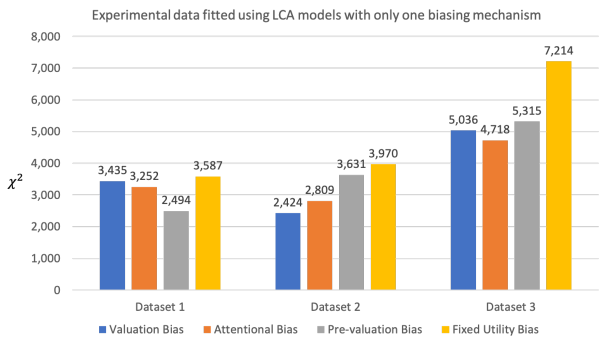

Figure 5: χ^2 fit statistics of LCA models each with one biasing mechanism. The values for the model with attentional bias are similar to those for the model with valuation bias.

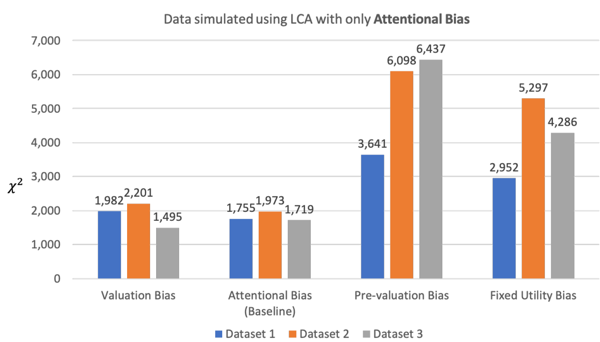

Figure 6: χ^2 fit statistics of LCA models with one biasing mechanism fitted onto data simulated using LCA with attentional bias. As suggested by the small χ^2 values, the model with valuation bias is able to fit simulated data well.

Conclusion

In this study, we aimed to develop a better understanding of the mechanisms underlying high rates of rejection in mixed gambles along two dimensions: by analyzing data from studies that have not been analyzed yet and by performing novel analyses about the role and nature of valuation bias. Our findings are largely consistent with those of Zhao et al. (2020): we find that most participants show a pre-valuation bias toward rejecting gambles, and pre-valuation bias is correlated to their overall tendency to reject gambles (i.e., rejection rates). However, we feel that the importance of valuation bias in mixed gambles may not have been highlighted sufficiently in the DDM literature: our analyses show that it plays an important role in understanding people's choice patterns

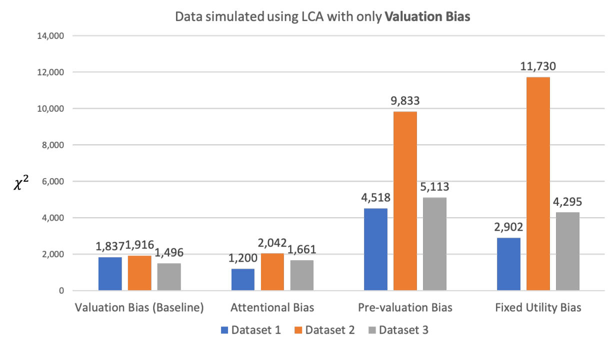

Figure 7: χ^2 fit statistics of LCA models with one biasing mechanism fitted onto data simulated using LCA with valuation bias. As suggested by the small χ^2 values, the model with attentional bias is able to fit simulated data well.

as a function of the gamble. Studies about loss aversion often favor one mechanism over others (Gal & Rucker, 2018), whereas our findings indicate that both mechanisms play an important role and pertain to distinct aspects of behavior, an effect that is consistent across data from three experiments.

We also empirically tested Zhao et al. (2020)'s claim that λ_{LR} computed from choice data using logistic regression might reflect people's degree of pre-valuation bias rather than valuation bias, since this could have serious implications for how the effects of various psychological, clinical, and neurobiological variables on loss aversion are interpreted. We found that while λ_{LR} from logistic regression is related to all parameters of the DDM, it shows the strongest relationship with valuation bias, further highlighting the importance of valuation bias in understanding human choices.

Finally, we observed strong mimicking between models with valuation bias and attentional bias, suggesting that behaviors that seem to arise due to valuation bias could also be explained by an attentional bias. This is also supported by experimental findings by Sheng et al. (2020) showing that valuation bias is linked to preferential gaze towards loss values. These findings are also a step toward bridging the computational frameworks of prospect theory and evidence accumulation models (Zilker & Pachur, 2021). Future research should focus on better understanding the relationship between valuation bias and attentional bias, and their effect on loss aversion.

Our analyses were restricted to decisions under equiprobable mixed gambles. Further research should focus on a broader range of judgment and decision-making tasks. Computational studies on the effect of various contextual factors – such as the framing of gambles – on behavior would also be very interesting. In particular, Ert and Erev (2013) have shown that the effect of status quo bias can reduce if gambles are framed in a particular way, and future studies could study this setting using the drift-diffusion model.

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