Testing Potential Mechanisms of the Description-Experience Gap in Loss Aversion

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Abstract

Recent research has found a novel description-experience gap in loss aversion, such that the overweighting of losses relative to gains in risky choice is more pronounced when people make decisions based on experienced rather than on descriptive summary information. Here, we tested two possible mechanisms of this gap: a *decision-by-sampling* (DbS) account, according to which the relative distributions of gain and loss outcomes that the decision maker encounters differ between description and experience; and an *optional stopping* account, according to which the role of losses for stopping information search differs between description and experience. Neither of the two mechanisms explained the gap. Whereas in description the relative rank of losses was higher than that of gains, this pattern was not more pronounced in experience (in fact, it was even reversed)—at odds with a DbS account. Further, although individual differences in the tendency of search termination after encountering a loss (vs. a gain) showed some association with individual-level loss aversion, this mechanism did not mediate the description-experience gap in loss aversion. Our results clarify that two prominent mechanisms of preference construction are unlikely to contribute to the description-experience gap in loss aversion, clearing the view on potential contributions of alternative mechanisms (e.g., asymmetric learning of gains and losses).

Keywords: loss aversion; description-experience gap; risky choice; decision by sampling; optional stopping; search termination

Introduction

Loss aversion is a key concept in decision science, referring to the assumption that when evaluating options that can lead to both gain and loss outcomes (e.g., mixed gambles), humans seemingly overweight losses: *"Losses loom larger than gains"* (Kahneman & Tversky, 1979, p. 279). Loss aversion is formalized in cumulative prospect theory's (CPT) value function, which transforms objective outcome values into subjective utilities (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), and where the steepness of the function in the loss domain relative to the gain domain indexes the degree of loss aversion (see Equation 3 below for a formal description). Although not uncontroversial (e.g., Yechiam, 2019), evidence for loss aversion has been found across various choice situations (Brown et al., 2024; Tversky & Kahneman, 1992), and both in riskless contexts (Mrkva et al., 2020) and in decisions involving risk (Walasek et al., 2024).

Whereas for decades research on loss aversion in risky choice has focused on choice paradigms in which people are presented with explicitly described information about the options' payoff structure (decisions from description; DfD), recently researchers have begun to also examine it in contexts in which information on the choice options is more uncertain. For example, in *decisions from experience* (DfE), people initially have no information about the options' payoff distributions but can learn about their reward structures by freely drawing samples from otherwise unlabeled options, before making a final, consequential choice (the sampling paradigm; see Figure 1; Hertwig & Erev, 2009).

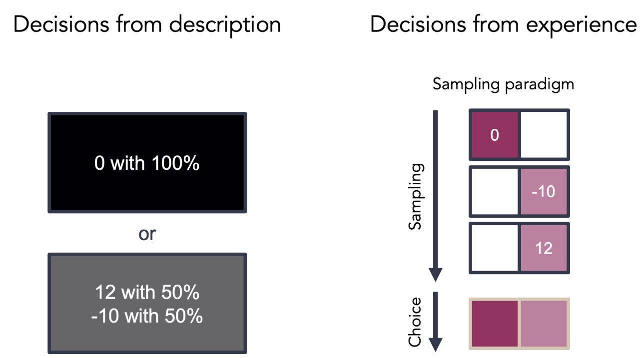

Figure 1: Schematic illustration of the choice procedure in decisions from description (left) and decisions from experience (right). At each trial, participants make one consequential choice in each choice problem.

Strikingly, recent research has revealed a *description-experience gap* in loss aversion, such that loss aversion seems to be more pronounced in experience-based choice (investigated with the sampling paradigm) than description-based choice (Busch & Pachur, 2024, in prep.). Here, we use data from a large-scale study to examine two candidate mechanisms that may underlie this gap. One mechanism is based on decision-by-sampling theory (DbS; Stewart et al., 2006), which assumes evaluative rank comparisons of option characteristics to all attributes of a current decision context. Consequently, the evaluation of options is influenced by the distribution of encountered numeric values in the decision context, which might differ between description- and experience-based choice. The other mechanism focuses on the notion of optional stopping in information search (Pachur & Scheibehenne, 2012; Spektor & Wulff, 2024); we examine

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whether people's search termination might be more sensitive to encountering a loss in experience-based than in description-based choice, which could give rise to differences in choice via a recency effect. In short, whereas DbS implies differences between gains and losses in the full distribution of samples, an optional stopping mechanism predicts differences between description and experience in the relative representation of losses only in the final drawn samples.

Analysis I: Decision by Sampling

In DbS theory (Stewart et al., 2006), it is assumed that the decision maker evaluates options based on binary ordinal comparisons (higher vs. lower) of the options' attribute values to other encountered attribute values. As a consequence, the subjective value of an outcome is a function of its relative rank among the other outcomes in a given choice context. For instance, the outcome of \$12 has a subjective value (relative rank) of 2/5 if the other possible outcomes in the choice context are \$5, \$10, \$20, \$25, and \$50, because \$12 would "win" in two of the five possible binary comparisons; by contrast, in a context with outcomes of \$5, \$20, \$25, \$35, and \$50, the subjective value of \$12 would be 1/5. DbS has also been proposed as a possible contributor to loss aversion (Walasek & Stewart, 2015, 2019). Walasek and Stewart (2015) manipulated the ranges of losses and gains, and produced loss aversion, loss neutrality, and even an underweighting of losses in people's choices (but see André & De Langhe, 2021; Forsgren et al., 2025).

Since information is provided in different formats in experience-based vs. description-based paradigms, the distribution of samples available in memory that are compared to given outcomes might differ accordingly, potentially giving rise to the description-experience gap in loss aversion. Specifically, whereas in description people may encounter each possible outcome type of a choice problem equally often (e.g., assuming unbiased box inspections in a Mouselab design, see below), in experience they encounter the outcomes depending on the latent probability distribution. This may lead to systematically different sampled distributions of gains and losses relative to description, against which losses and gains obtain different relative ranks. For instance, if choice problems include low-to-moderate losses with relatively high probability, losses might tend to receive higher relative ranks in experience than in description, thus contributing to a description-experience gap in loss aversion. Crucially, we test whether this holds even when the outcome ranges (i.e., minimum and maximum losses and rewards) are the same.

Method

To test this possibility, we reanalyzed data from a recent large-scale online study (total N = 408; M_{age} = 26.55; SD_{age} = 6.06; $Range_{age}$ =18 to 69 years), run through a university participant pool, comprising a multi-ethnic group of students and other local residents of varying occupations (Busch & Pachur, in prep.). Each participant was presented with 51 two-option, mixed-domain lottery choice problems, either in an experience condition implemented in the sampling paradigm, or a description condition, in which the problems were shown in a PsychoPy implementation of Mouselab (cf. Pachur et al., 2018). Outcomes in the gambles ranged from -1000 to +990. In the experience condition, participants could freely sample from two options before making a final, consequential choice. In the description condition, participants had explicit information about the possible outcomes and their corresponding probabilities, but this information was hidden behind boxes and could be revealed by mouse click. In the following, we refer to these box inspections as (external) sampling in description. On average, people drew M = 27.83 samples per choice problem in the experience condition (SD = 26.52), and made M = 12.18 box inspections per problem in the description condition (SD = 7.61). Final choices were incentivized such that one of the chosen gambles was randomly selected at the end of the experimental session, played out, and the participant received a bonus payment based on the resulting outcome.

The relative rank of an outcome within its domain (gain vs. loss) was determined by its position in the empirical cumulative distribution of outcomes in the same domain sampled by a given participant. If the same outcome was sampled multiple times, these were counted as separate observations for the empirical cumulative distribution. For fitting multilevel beta regressions, relative ranks r_i were rescaled to avoid values of 0 and 1 (according to Smithson & Verkuilen, 2006).

As a measure comparing the relative ranks of gains and losses, we computed an index Δ_j (for each participant j) that expressed the log-transformed ratio of the average (across choice problems) relative rank of loss outcomes $\overline{r_j^-}$ to that of gain outcomes $\overline{r_j^+}$:

$$\Delta_j = log\left(\frac{\overline{r_j^-}}{\overline{r_j^+}}\right). \tag{1}$$

To measure each participant's loss aversion, we modeled their choices with a Bayesian hierarchical implementation of CPT in JAGS (Hellmann et al., 2025; Scheibehenne & Pachur, 2015). In CPT (Tversky & Kahneman, 1992) the subjective value V of an option with n gain and loss outcomes, x_i^+ and x_i^-, and corresponding probabilities p_i^+ and p_i^-, is given by

$$V(A) = \sum_{i=1}^{n} v(x_i^+)\pi^+(p_i^+) + \sum_{i=1}^{n} v(x_i^-)\pi^-(p_i^-). \tag{2}$$

$v()$ is a value function that transforms objective outcomes into subjective values:

$$v(x) = \begin{cases} x^\alpha, & \text{if} \quad x^+ \geq 0 \\ -\lambda(-x)^\alpha, & \text{if} \quad x^- < 0. \end{cases} \tag{3}$$

α indexes the curvature of the value function and λ the steepness of the function in the loss relative to the gain domain, with $\lambda > 1$ indicating loss aversion. π are decision weights, which are computed from the cumulative probabilities for the respective outcome (for details, see Tversky & Kahneman, 1992); the probabilities are transformed with the probability weighting function $w()$:

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}} \tag{4}$$

For a choice between two options A and B, the probability of choosing option A is then determined by a logit choice rule:

$$P(A) = \frac{1}{1 + e^{-\phi(V(A)-V(B))}} \tag{5}$$

In the hierarchical implementation of CPT, all parameters were estimated both on the individual and on the group level.

Results

A linear regression predicting individual λ_j estimates from the experimental condition (dummy coded, with description as reference) indicated a description-experience gap in loss aversion, with higher loss aversion in experience than in description, $b = 0.26$, $SE = 0.07$, $t(406) = 3.86$, $p < .001$. To test whether this gap can be accounted for by the log-transformed individual-level rank asymmetry index Δ_j, we ran another regression model that included both Δ_j and condition as well as their interaction as fixed effects. Figure 2 plots the individual-level estimates of λ as a function of the ratio of relative ranks for gains and losses, Δ. The effect of experimental condition on loss aversion did not decrease, $b = 0.55$, $SE = 0.15$, $t(404) = 3.67$, $p < .001$, suggesting that the description-experience gap in loss aversion is not driven by a DbS mechanism.

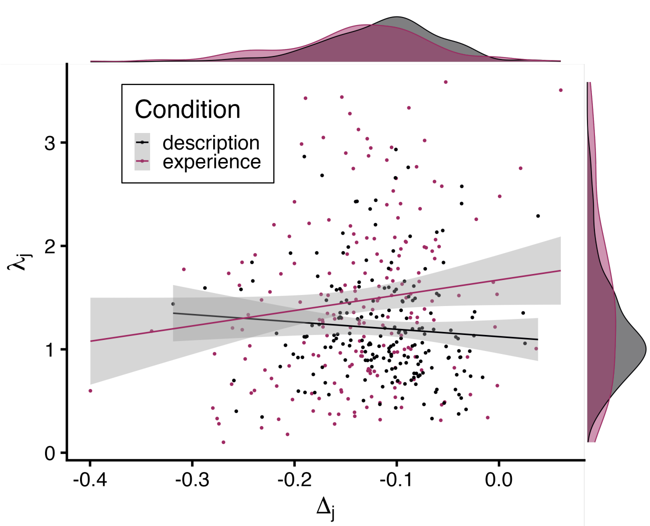

Figure 2: The relationship of domain rank asymmetries of outcomes (Δ_j) with loss aversion (λ_j) by condition (colored). Individual differences in loss aversion are only explained by the condition (i.e., description vs. experience), but not by rank asymmetries between domains.

In addition, individual-level loss aversion was unrelated to the individual-level relative ranks of outcomes, $b = 0.71$, $SE = 0.85$, $t(404) = 0.84$, $p = .40$. There was an interaction between rank asymmetry and condition, $b = 2.20$, $SE = 1.08$, $t(404) = 2.04$, $p = .04$, with a significant positive association of λ and Δ in experience, $b = 1.48$, $SE = 0.66$, $p = .03$, but not in description, $b = -0.71$, $SE = 0.85$, $p = .40$.

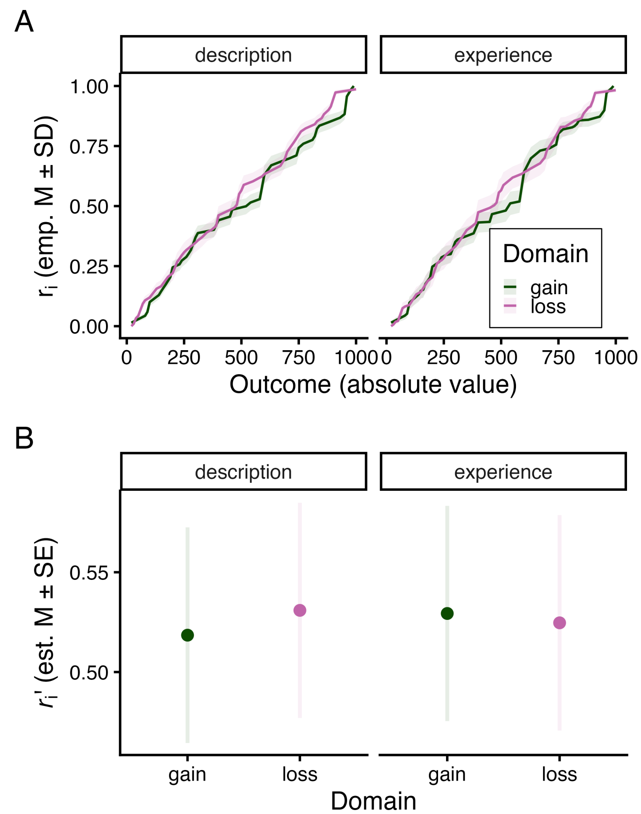

Figure 3: A: Relative ranks of each outcome magnitude based on the individual-level empirical cumulative distribution function within the gain and loss domain, separately for the description and experience conditions. B: Predicted relative rank of gain and loss outcomes in description and experience.

To further unpack these results, we compared the difference in the relative ranks of losses and gains between description and experience. Figure 3A displays the relative ranks of a given outcome magnitude (with their SDs) in the gain and loss domains, separately for the description and the experience conditions. We statistically compared differences in the relative rank of gain and loss outcomes using a multilevel beta regression with a logit link function, predicting the rescaled relative rank of an outcome r_i' across participants by its (gain vs. loss) domain (sum-coded with gain = 1 and loss = -1), by the experimental condition (dummy coded, with description as reference), as well as by their interaction, and including random intercepts for the objective absolute outcome value level and for participants.

Figure 3B plots the relative ranks for gains and losses, separately for the description and experience conditions. There was an overall main effect of outcome domain: on average, gain outcomes tended to have lower relative ranks than loss outcomes, $b = -0.025$, $SE = 0.001$, $z = -19.68$, $p < .001$. There was no main effect of condition, $b = 0.010$, $SE = 0.012$, $z = 0.76$, $p = .446$. However, there was also an interaction between domain and condition, $b = 0.034$, $SE = 0.001$, $z = 24.49$, $p < .001$: Whereas the relative ranks were higher for losses (than for gains) in the description condition, in the experience condition there was the opposite pattern, with relative ranks being slightly higher for gains than for losses.

Summary

How encountered outcomes rank in the distribution of other outcomes in a given decision context has been proposed as a key contributor to loss aversion (Walasek & Stewart, 2015, 2019). We tested whether this ecological mechanism might help explain the description-experience gap in loss aversion. Although the relative ranks for losses were higher than those for gains in the description condition, this was not the case in experience. Here, losses had lower relative ranks than gains, which—according to DbS—would predict the opposite direction for our observed description-experience gap, with *lower* rather than higher loss aversion in experience. We conclude that the description-experience gap in loss aversion does not seem to be driven by the DbS mechanism.

Analysis II: Optional Stopping

The second mechanism we considered as a potential driver of the description-experience gap in loss aversion is *optional stopping*: Decision makers may be more likely to terminate external sampling after encountering outcomes of a particular type. This would then lead to an overrepresentation of this type of outcome in recently drawn samples, which may in turn influence choice behavior via a recency effect. Previous research has found optional stopping with regard to rare (low probability) outcomes, with frequent termination of search after sampling rare events (Spektor & Wulff, 2024). Optional stopping has also shown to be a contributor to the endowment effect, the phenomenon that people value an object more highly when they own it (from a seller's perspective) than when they do not own it (from a buyer's perspective). Pachur and Scheibehenne (2012) showed that buyers stopped sampling more often after encountering low (vs. high) outcomes, whereas sellers terminated search after encountering high outcomes—helping to explain that the endowment effect is somewhat more pronounced in experience than in description.

In a similar vein, people might be more likely to terminate search after encountering a loss than after encountering a gain. If so, this would lead to an overrepresentation of losses in the final window of drawn samples, making choices more sensitive to losses than to gains due to the impact of recently drawn losses. This pattern could be stronger in experience than in description. Whereas in description-based choice, sampling (i.e., a box inspection) of a loss is largely intentional (as the domain of an outcome is known after its first inspection), in experience, people do not know which outcome domain they will encounter (because the sample is drawn randomly from the underlying payoff distribution). As a result, the (arguably affective) experience of encountering a loss may be more likely to terminate search in experience than in description. Consequently, the relative representation of losses in last drawn samples before a choice could differ between the conditions, potentially contributing to the description-experience gap in loss aversion.

Method

We again reanalyzed data from Busch and Pachur (in prep.) , as described in more detail in the Method section of Analysis I: Decision by Sampling. Computational modeling with CPT followed the same approach described there.

The individual-level relative representation of losses vs. gains in the window of samples right before a choice was quantified with an index β_j, which was computed based on the difference between the log-transformed individual-level average observed ratio of the proportion of losses $\hat{p_j}^-$ to that of gains $\hat{p_j}^+$ within the final set of sampled outcomes, and the average log-transformed base-rate probability ratio to sample a loss p_c^- relative to that of a gain p_c^+ in a given condition c, as

$$\beta_j = log\left(\frac{\hat{p_j}^-}{\hat{p_j}^+}\right) - log\left(\frac{p_c^-}{p_c^+}\right). \quad (6)$$

We computed β_j for four different window sizes of samples before the final choice: The last drawn sample, the last two, the last three, or the last four samples. Outcomes of zero were not counted towards gains or losses.

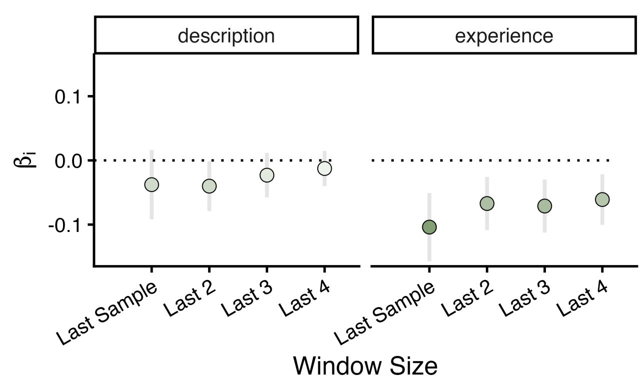

Figure 4: Optional stopping after sampling losses (vs. gains) relative to the base rate across all four window sizes. The y-axis displays the average log-transformed ratio of the ratio β_i relative to the baseline probability ratio to encounter a loss (vs. a gain) outcome. Positive values indicate an overrepresentation of losses in the final window, and negative values indicate an overrepresentation of gains.

Results

Figure 4 displays β_i, the log-transformed ratio of the empirical mean ratios of losses and gains relative to the base-rate probability ratio to encounter a loss vs. gain outcome, separately for different window sizes of the final samples. Whereas in the description condition there was the same number of boxes containing losses vs. gains, making it a priori equally likely to sample a loss or a gain (thus resulting in a base-rate ratio of $log(\frac{p_c^-}{p_c^+}) = 0$), in the experience condition it was slightly more likely to sample a gain than a loss across choice problems, $M(log(\frac{p_c^-}{p_c^+})) = -0.04$). Note that in experience, the base-rate depended on the latent payoff distributions.

Note also that individual-level loss ratios in final samples β_j and the DbS rank asymmetry index Δ_j were uncorrelated, $b = 0.00$, $SE = 0.02$, $t(406) = .55$, $p = .56$, demonstrating the independence of the DbS and the optional stopping mechanisms.

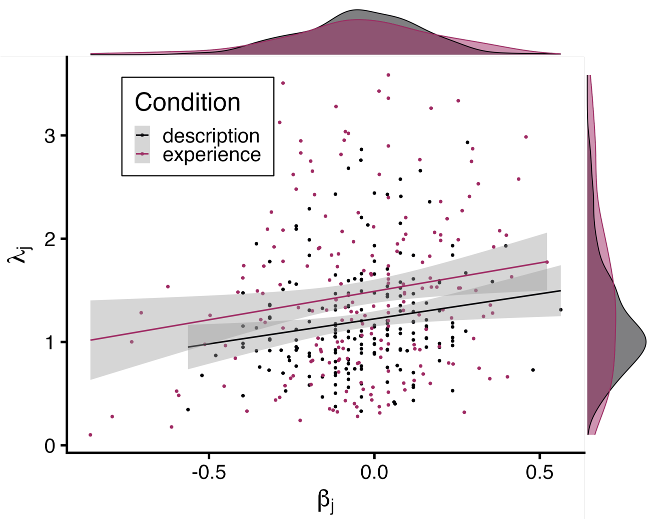

Figure 5: The relationship of relative loss representations in last two samples β_j with loss aversion λ_j by condition (colored). Individual differences in loss aversion are explained independently by the condition effect as well as individual-level asymmetries in optional stopping.

To test whether individual differences in β may help explain the description-experience gap in loss aversion, we ran a linear regression predicting individual λ_j estimates by the experimental condition and the log-transformed individual-level loss ratio index β_j, with their interaction included. The effect representing the description-experience gap in loss aversion (see Analysis I: Decision by Sampling) was not lower than when β was not included, $b = 0.27$, $SE = 0.07$, $t(404) = 3.89$, $p < .001$. The individual-level loss ratio in the window of final samples (here we focus on window size of 2) was only weakly, if at all, related to individual-level loss aversion, with a higher loss ratio being slightly associated with higher loss aversion, $b = 0.49$, $SE = 0.26$, $t(404) = 1.87$, $p = .06$. This also held for different window sizes of β_j (with $p = .07$ when aggregating across the last 3 samples, $p = .03$ when aggregating across the last 4 samples; but when considering only the very last sampled outcome, there was clearly no association, $p = .35$). There was no interaction between β_j and condition, $b = 0.07$, $SE = 0.32$, $t(404) = 0.32$, $p = .84$ (see Figure 5).

Summary

We find no evidence that people are more likely to stop sampling after encountering a loss than after encountering a gain, and that this pattern is more pronounced in experience than in description; if anything, people were more likely to stop after encountering a gain than after encountering a loss outcome. This holds across both description and experience, with the experience condition even showing a higher overrepresentation of gains in final samples than the description condition. Despite this overall gain bias, the relative representation of losses in recent samples showed a weak link to loss aversion, independent of learning condition. We conclude that the description-experience gap is unlikely to be due to biases in search termination.

Discussion

We tested two candidate mechanisms that may underlie the description-experience gap in loss aversion. A decision-by-sampling mechanism has previously been proposed to be a key contributor to loss aversion (Walasek & Stewart, 2015, 2019). Here, we tested whether the DbS account also holds in decisions from experience, and, more importantly, whether it may help explain the description-experience gap in loss aversion. Although in both conditions participants' choices indicated loss aversion, the relative ranks of losses were higher than those of gains only in the description condition. In fact, in the experience condition gains had slightly higher relative ranks, which according to DbS theory should lead to gain seeking (i.e., the opposite of loss aversion). Overall, a DbS mechanism thus does not seem to be the driving mechanism behind the description-experience gap in loss aversion. Further, although individual differences in rank asymmetry between the gain and loss domain were associated to people's loss aversion in experience-based choices, no such pattern was evident in description-based choices. This aligns with recent findings that challenge the DbS mechanism for description-based risky choice (Forsgren et al., 2025). However, future studies examining a DbS mechanism for loss aversion may also consider the possibility that people compare currently sampled outcomes only to subsets of previously encountered outcomes (e.g., due to memory biases, Hotaling et al., 2022).

As a second mechanism, we tested systematic tendencies in search termination after encountering losses. We found no indication for optional stopping after encountering a loss, and instead evidence for a tendency to terminate search after encountering a gain. At odds with an optional stopping account for the description-experience gap in loss aversion, the ratio of loss to gain outcomes in the final window of encountered outcomes was not higher in the experience than in the description condition—in fact, there was even the opposite pattern. We conclude that the description-experience gap in loss aversion is unlikely to be caused by a specific sensitivity in search termination to losses. This aligns with the observation that also the classical description-experience gap in probability weighting persists when samples cannot be freely drawn (and optional stopping thus cannot play a role; Rakow et al., 2008).

At first glance, our observed tendency of optional stopping after gains seems to be inconsistent with evidence that losses loom larger than gains in choice. How to reconcile these findings? One possibility is that sampling a loss leads to continued exploration (e.g., Lejarraga et al., 2012), making it more likely that search is terminated after sampling a gain outcome. After the sampling stage, however, losses may exert a stronger influence at the evaluative stage, leading to overall loss aversion in choice behavior. Another possibility is an optimistic positivity bias (e.g., Palminteri & Lebreton, 2022): People may prefer to terminate search only after a positive (rewarding) sampling encounter rather than after a loss, to retain a positive overall experience that may be independent of their choice.

Nevertheless, even though gains were overall more prevalent than losses in people's final window of sampled outcomes, the ratio of losses to gains in the final window was associated with individual differences in loss aversion—across both experience and description. That is, individuals whose recent samples contained relatively more losses tended to exhibit higher loss aversion in subsequent choices. Thus, although optional stopping does not seem to produce loss aversion at the aggregate level, a less pronounced focus on gains for search termination seems to be associated with higher loss aversion at the individual level. It is worth emphasizing that the causal direction of this association requires further investigation. Whereas it may indeed be that an (experimentally manipulated) overrepresentation of losses in recent samples causally induces higher loss aversion (Pachur et al., 2018), an alternative explanation is that people with higher (trait) loss aversion also tend to stop sampling more often after encountering losses, influencing both sampling behavior and final choices.

What may drive the description-experience gap in loss aversion if not a DbS or an optional stopping mechanism? Fruitful future directions include the investigation of asymmetric learning, which has been demonstrated to modulate loss aversion estimates (Haines et al., 2023), and attentional mechanisms, that might differ between description and experience (e.g., Chow et al., 2025).

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