Modeling value integration during decision making under uncertainty: The Florida-and-Georgia (FLAG) gambling task

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Abstract

Humans frequently make decisions that involve repeated interactions under uncertain conditions in everyday life. A constellation of cognitive biases may drive such decisions. To investigate how these biases influence decision making by potentially altering how values are integrated across trials, we developed a novel paradigm—the **Fl**orida-**A**nd-**G**eorgia (FLAG) gambling task. In the FLAG task, 170 young adult participants chose between a deck, which yields variable outcomes, and a sure-thing offer. This approach allows us to model value integration as influenced by both learning processes (e.g., primacy-recency bias) and key factors drawn from Prospect Theory, including sensitivity to outliers and loss aversion. Our findings reveal that individuals in their decision making underweight outliers for both gains and losses and are biased by recent outcomes, but we found no evidence of loss aversion. The FLAG task strives to strike a balance between ecological validity and experimental control, providing insights into the cognitive processes involved in decision making. In closing, we discuss future directions for the FLAG task and its potential societal and clinical applications.

Keywords: decision making, computational modeling, Prospect Theory, individual differences

Author summary

People often make choices without knowing their outcomes, and these choices are often shaped by cognitive biases such as sensitivity to outliers, loss aversion, and primacy-recency effects. To probe how these biases influence decision making, we developed the Florida-And-Georgia (FLAG) gambling task, in which participants chose between a sure-thing offer and a gamble with unknown outcomes. Using models inspired by Prospect Theory, we found that participants undervalued large gains but overvalued large losses, consistent with Prospect Theory. Participants also focused more on recent outcomes, showing a recency bias. Notably, we did not observe the expected loss aversion. The FLAG task offers a valuable tool to examine how learning and memory interact with features of Prospect Theory to guide decision making under uncertainty. Our findings could inform efforts to address decision deficits in aging, mental health, and real-world choices in finance and healthcare.

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Introduction

Imagine you are making a financial investment decision between two options: One option involves a variable portfolio, which yields variable returns with unknown probabilities. You have information about its annual returns over the past five years. The other option is a stable financial instrument, which yields a guaranteed positive return, although the magnitude of this positive return may vary, depending on whether it is a saving account, a high yield certificate of deposit account, or a retirement plan. Which option would you choose?

Everyday decision making like this necessitates multiple psychological (e.g., cognitive, motivational, and affective) processes to work in concert to guide behavior. Individuals with impaired cognitive capacities due to either clinical conditions or normal aging, face challenges in making adaptive decisions in complex decision-making tasks [1,2]. For decades, psychological research has been trying to understand the underlying mechanisms of decision deficits in both clinical and aging populations.

Experimental studies traditionally employ monetary gambles as a pragmatic tool for studying human decision making, such as in the framing effect [3] and the loss aversion effect [4]. Inspired by decision-making theories such as Prospect Theory [4], these tasks typically involve choosing between two gambling options, with outcomes and probabilities either explicitly described or learned through repeated interactions [5]. Although valuable for revealing how individuals value gains and losses and weigh different probabilities, these tasks often limit each option to two possible outcomes [6,7]. This simplified setup overlooks the complexity of

real-life decisions, in which choices often yield more than two outcomes that demand value integration across multiple possibilities [8].

In contrast, the Iowa Gambling Task [IGT; 9] presents a broader range of outcomes, including both gains and losses of varying magnitudes, which reflects how real-world decision options may simultaneously lead to gains and losses. The IGT can also be used to examine learning-based value integration as it involves iterative choices, and has been able to distinguish decision impairments in aging [10] and clinical populations [11] that experience learning and memory impairments. Nevertheless, the very complexity that makes the IGT more ecologically valid also introduces challenges to interpreting behavior. Tasks such as the IGT often engage participants in multiple cognitive processes, whose impacts on decision making are difficult to isolate [12].

For example, three key features of the IGT can complicate the interpretation of behavior. First, performance is confounded by stimulus-response contingency and interdependencies between cognitive, motivational, and response processes [1]. The intertwined relationship between choices and stimuli makes it difficult to determine whether decisions are driven by cognitive mechanisms or immediate stimulus-response contingency. Second, reward and punishment probabilities in the IGT change over time, leading participants with different exploration-exploitation tendencies to adopt different strategies (e.g., win-stay/loss-shift and reinforcement learning), further obscuring the interpretation of behavior [12]. Finally, the IGT does not fully capture real-world decision dynamics, such as the influence of large positive outliers (e.g., high yield in buying a stock), since only negative outliers are present in the IGT. This limits its ability to examine how the sensitivity to extreme positive outcomes influences decisions. In summary, *the IGT engages participants in a wide variety of cognitive processes —*

such as learning, memory, risk-taking, ambiguity seeking, and gain-loss processing—making it challenging to disentangle these processes in a brief, unbalanced design. Therefore, although valuable for examining potential mechanisms of decision-making deficits [1,11], the IGT falls short as a quantitative tool for precisely isolating the cognitive components underlying decision making.

In this context, research highlights three key cognitive components underlying decision making— ***sensitivity to outliers***, ***loss aversion***, and ***primacy-recency*** bias. *Sensitivity to outliers* affects how people respond to extreme gains or losses, with high-frequency gains often outweighing large losses, evident in preferences for certain risky options [13]. *Loss aversion* refers to the tendency to weigh losses more heavily than equal-sized gains [4,14]. Furthermore, when evaluating choice options, decision-makers integrate gains and losses into an overall subjective value, or "utility", which shapes choices [15,16]. Memory plays a crucial role in the value integration stage of decision making [17,18], with earlier or more recent outcomes disproportionately influencing choices [19,20], resulting in *primacy and recency biases* [21].

Based on these findings, we focus on three cognitive biases—sensitivity to outliers, loss aversion, and primacy-recency bias—in modeling experience-dependent decision making under uncertainty. Computational modeling has been increasingly applied to behavioral data to delineate the psychological processes underpinning decision making and to inform clinical applications in decision deficits [22,23]. Nevertheless, tasks such as the IGT were not designed with computational models in mind, limiting their utility in identifying individual cognitive components.

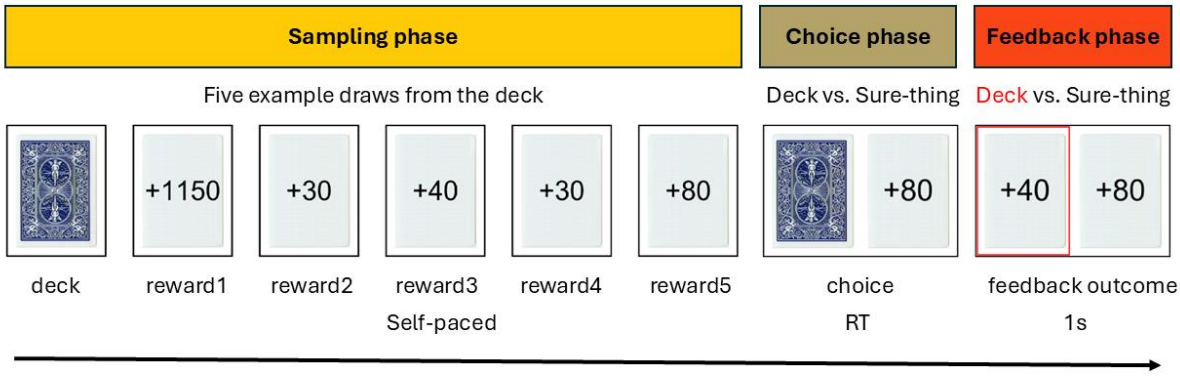
To begin to address these limitations, we developed a computational modeling-compatible task—the Florida-And-Georgia (FLAG) gambling task. During the task, participants

completed 100 trials, each involving a single decision between a variable outcome and a sure-thing offer, in the format of a gambling game. During each game (Fig 1), participants first drew five examples from the deck (**Sampling phase**) before choosing between drawing another card from the deck and the sure-thing offer (**Choice phase**). After selecting either the deck or the sure-thing offer, the value of the chosen card was revealed (**Feedback phase**).

Unlike prior tasks such as the IGT, which engage in multiple psychological processes but struggle to disentangle their effects, the FLAG task simultaneously examines and isolates the effects of multiple cognitive biases in decision making. By symmetrically varying both the magnitude and frequency of gains and losses across a large number of decks (100), the FLAG task effectively applies computational modeling to decompose decision making into distinct components. In so doing, it provides a more precise and comprehensive understanding of how these cognitive biases interact to shape decisions.

Fig 1

Schematic of the FLAG Task



Note. Participants were presented with a deck of cards and a sure-thing offer (Choice phase). Before making their decision, they drew five example cards from the deck, with card values centered around an average score (Sampling phase). After selecting either the deck or the sure-

thing offer, the value of the chosen card was revealed (Feedback phase). The task aimed to examine participants' decision making under uncertainty, based on potential variability in outcomes from the deck versus the sure-thing/guaranteed offer.

As brief glimpse of our findings, we applied computational cognitive models to disentangle the roles of sensitivity to outliers, loss aversion, and primacy-recency bias in the FLAG task. Our models revealed a concave utility curve for gains and a convex utility curve for losses, consistent with Prospect Theory [4]. In addition, we found that most participants placed greater weight on recent outcomes, demonstrating a recency bias. Nevertheless, we did not observe loss aversion, suggesting that it may not be as robust when other decision-making features are simultaneously at play. Finally, parameter recovery analyses indicated that the FLAG task exhibits favorable computational properties, successfully isolating individual cognitive components involved in decision making. These findings collectively support the effectiveness of our approach in achieving the study's aim.

Results

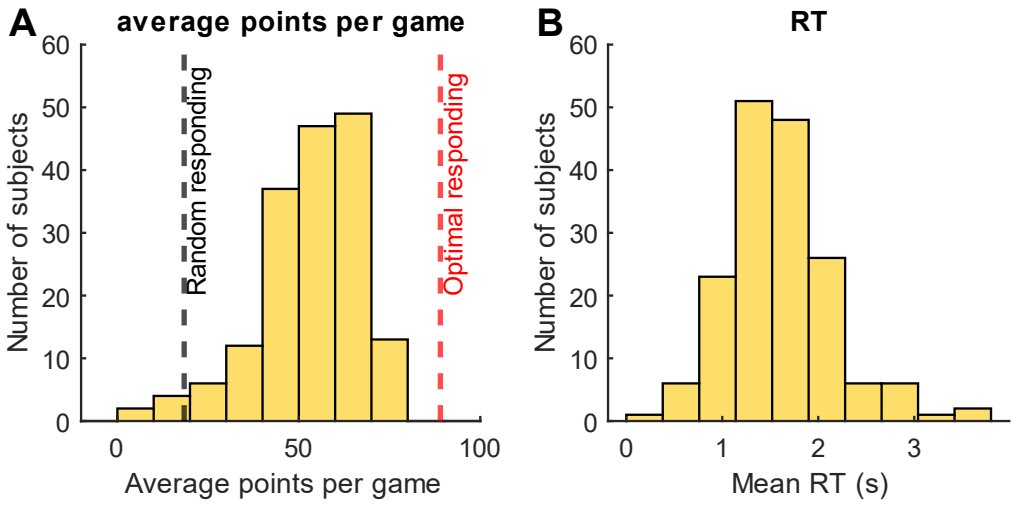
Basic task performance

Most participants (166 of 170) performed the task at better than chance levels, making 54 points (SD = 14; out of 89 max) per game on average (Fig 2A). T-test results indicated that the average points per game were significantly higher than the average points (18.4) earned by random responding ($t(169) = 32.67$, $p < .0001$). The effect size, as measured by Cohen's d, was 2.51, indicating a large effect. The mean response time for the decision between the deck and the known outcome was 1.6 seconds (SD = 0.6) (Fig 2B). Over the course of the task, participants

made increasingly optimal choices by choosing the option that yielded higher payout and responded faster over time (Appendix A).

Fig 2

Basic Performance in the FLAG Task



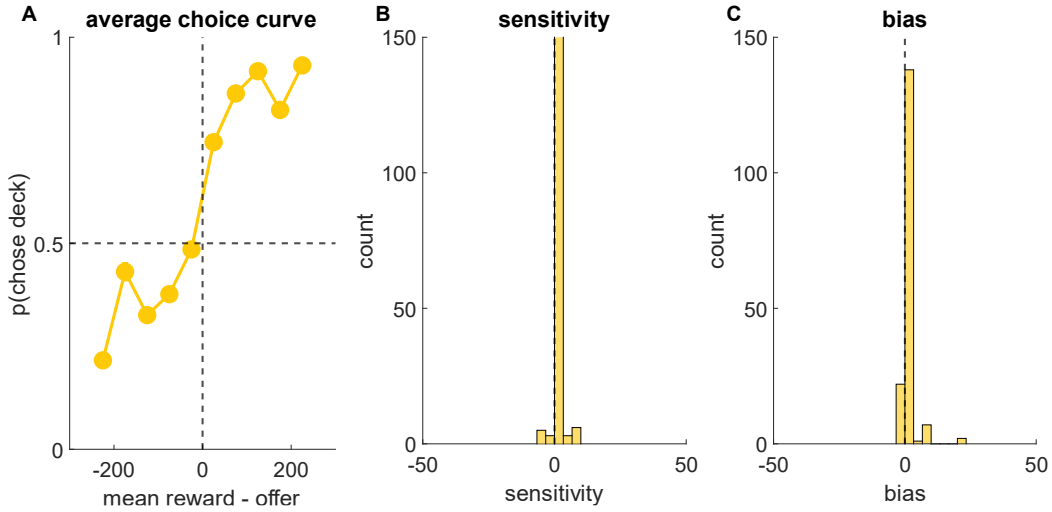
Note: (A) Distribution of points per game, where the black dashed line represents the average points (18.4) earned by random responding, and the red dashed line represents the highest possible average points (89) that can be achieved by making optimal decisions in the task; (B) Distribution of mean response time.

To ensure that responses were sensible, we first plotted an average choice curve based on aggregated data. As predicted, as the difference between the mean reward of the deck and the sure-thing offer increased, the probability of choosing the deck increased, supporting validity of responses (Fig 3A). We fitted individual choice curves to a sigmoid function using MATLAB's lsqcurvefit function to obtain individual measures of sensitivity and bias for each participant. Average sensitivity was .23 (SD = 1.58, CI [.03, Inf]), which was significantly greater than zero ($t(169) = 1.90$, $p = 0.03$ (right-tailed)), suggesting that participants' decisions were sensitive to changes in decision values and that participants remained attentive throughout the experiment

(Fig 3B). Average bias was 1.11 (*SD* = 2.79, CI [.69, 1.54]), which was significantly different from zero ($t(169) = 5.21$, $p < .001$ (two-tailed)), suggesting that participants were biased towards choosing the deck over the sure-thing offer in this task (Fig 3C).

Fig 3

Average Choice Curve, Sensitivity, and Bias



Note: (A) Probability choosing deck as a function of the difference between mean deck reward and the sure-thing offer value. The horizontal dashed line represents randomly choosing between the deck and the sure-thing offer, and the vertical dashed line represents the mean reward of the deck being identical to the sure-thing offer. (B) Distribution of individual sensitivity values, where the dashed line represents zero sensitivity, which corresponds to random responding; (C) Distribution of individual bias values, where the dashed line represents zero bias, which corresponds to no response bias for choosing either the deck or the sure-thing offer.

Cognitive model

Model parameters

Our model, inspired by Prospect Theory, assumed that participants compared the relative utilities of the deck and the sure-thing offer, choosing the option with higher expected utility. In this section, we briefly overviewed the key parameters across the Base Cognitive Model's four computational steps, as described in detail in Section "Base Cognitive Model."

Utility transformation. Rewards were transformed into subjective utilities based on a utility function. The parameters of interest here were $\boldsymbol{\eta_+}$and $\boldsymbol{\eta_-}$, which governed the curvature for gains and losses, respectively (Equation 1). These parameters helped to capture participants' sensitivity to outliers.

Utility of the deck. The expected utility of the deck was computed by weighing the utilities of each reward (Equation 2). The shape of these weights was determined by $\boldsymbol{\alpha}$, which controlled whether early (primacy) or later (recency) rewards were emphasized (Equation 3).

Equivalent reward. The utility of the deck was then transformed back into an equivalent reward. This step allowed for better comparison between utilities and rewards (Equation 4), ensuring the inverse temperature parameters in the decision rule (Step 4) were comparable across participants.

Decision rule. Finally, the model used a logistic function to determine the probability of choosing the deck versus the sure-thing offer, based on the difference between their equivalent rewards. Here, three key parameters came into play: $\boldsymbol{\beta_{side}}$ (side bias), $\boldsymbol{\beta_r}$ (the weight given to the reward difference), and $\boldsymbol{\beta_{safe}}$ (bias towards the sure-thing offer) (Equation 5 and 6).

By fitting these six parameters ($\boldsymbol{\eta_+}$, $\boldsymbol{\eta_-}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta_{side}}$, $\boldsymbol{\beta_r}$, and $\boldsymbol{\beta_{safe}}$), we gained insights into how participants perceived rewards, weighed gains and losses, integrated information over repeated interactions with the decks, and how consistently participants made choices during the task.

Model fit

After removing outliers (3 SDs above or below the mean), we plotted the distribution for each model parameter (Fig 4). In addition, we estimated the curvatures for gains and losses separately, computed their ratio as an index of loss aversion, and plotted this computed ratio (Fig 5). A concave curve for gains was found in 147 of 166 participants, with 48 participants exhibiting values near zero (i.e., < .001). T-test results indicated that on average, the curvature for gains parameter was significantly different from one (M = .52, SD = .58, CI = [.43, .60], $t(165)$ = -10.92, p < .0001), suggesting that most participants had a diminishing sensitivity to gains. The effect size, as measured by Cohen's d, was .85, indicating a large effect. A convex curve for losses was found in 160 of 168 participants, with 81 participants exhibiting values near zero (i.e., < .001). Twenty-four participants exhibited curvatures near zero (i.e., < .001) for both gains and losses. On average, the curvature for losses parameter was significantly different from one (M = .30, SD = .43, CI = [.23, .36], $t(167)$ = -21.12, p < .0001), suggesting that most participants had a diminishing sensitivity to losses. The effect size, as measured by Cohen's d, was 1.63, indicating a large effect. That is, most participants had a concave utility curve, in which both large gains and large losses were undervalued. Results from a paired t-test indicated that overall, there was a significant difference between the two curvatures with $\eta_+ > \eta_-$ (M = .24, SD = .52, CI = [.15, .32], $t(165)$ = 5.78, p < .0001), suggesting that participants may have been gain seeking rather than loss averse.

Fig 4

Histogram Of Parameter Values in the Base Cognitive Model with Outliers Removed

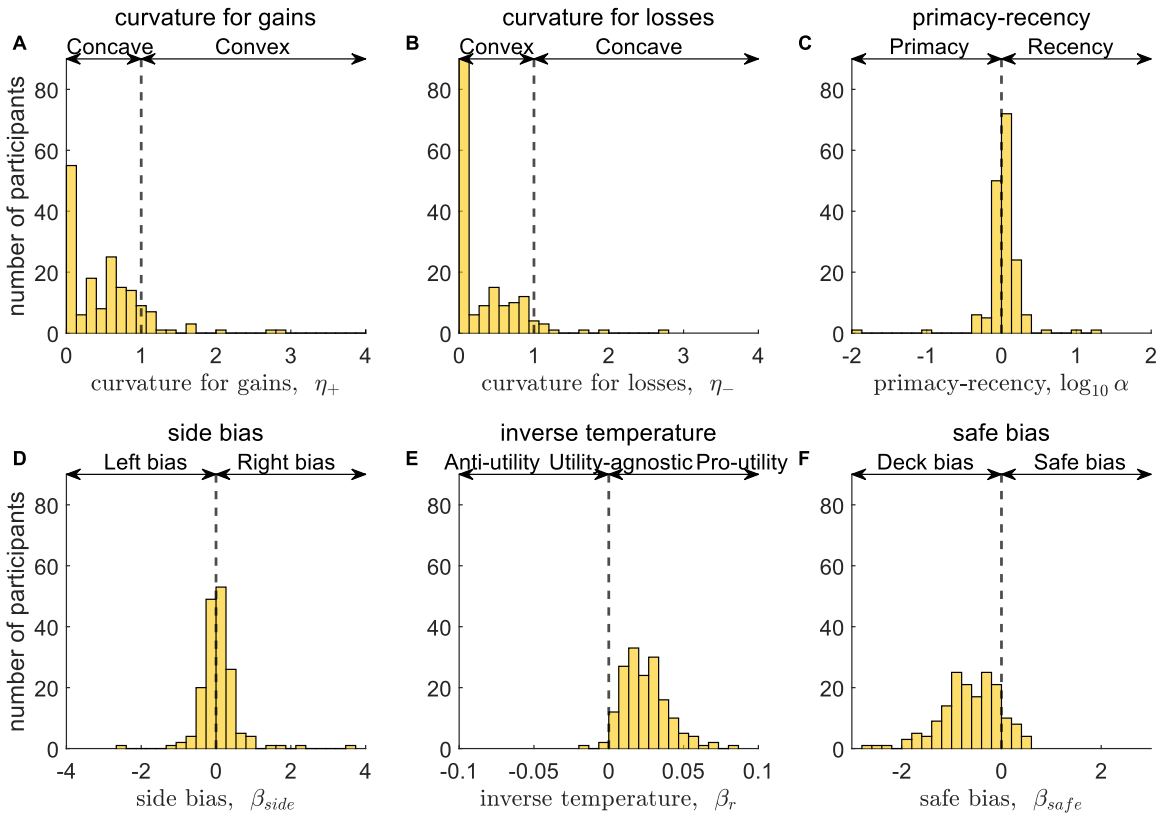
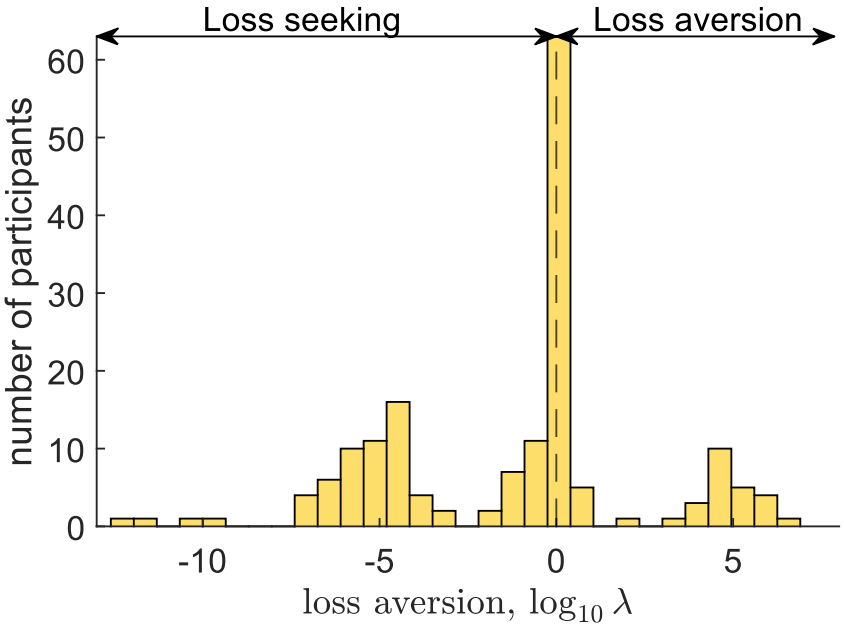


Fig 5

Histogram Of Computed Lambda Values (η_-/η_+) with Outliers Removed



Corroborating this possibility, the computed ratio of loss aversion (η_-/η_+) [24] was greater than one for 61 of 166 participants, suggesting that a relatively smaller proportion of participants weighed losses more heavily than gains. To correct for the skewness in the distribution of the loss aversion ratio, a log10 transformation was applied to the computed ratio of loss aversion (η_-/η_+). After transformation, the average log-transformed ratio (i.e., log10(1)) was not significantly greater than zero (M = -1.26, SD = 3.73, CI = [-1.74, Inf], $t(165)$ = -4.37, p = 1.00 (one-tailed)), suggesting that losses were not weighed more heavily than gains. In back-transformed terms, the average log-transformed ratio corresponded to a geometric mean loss aversion ratio of .05.

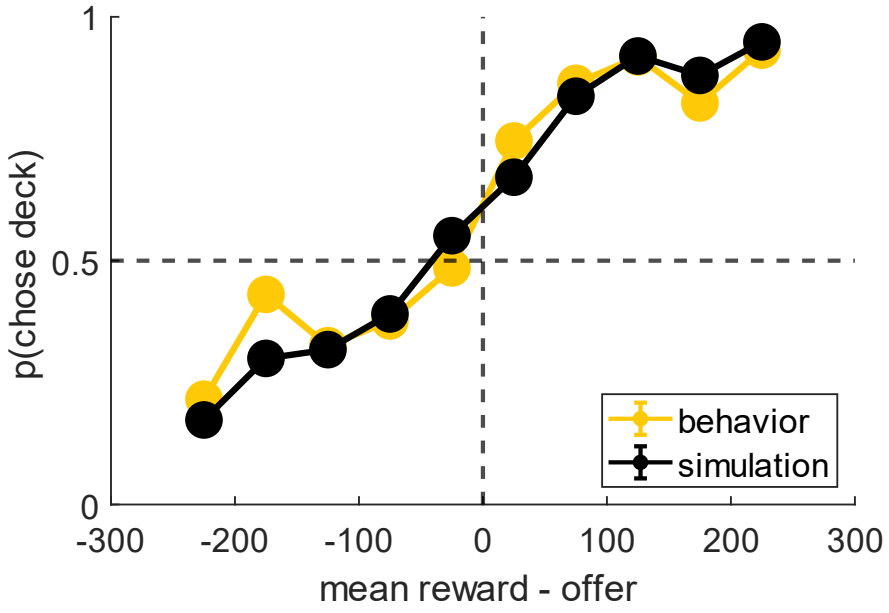
In addition, we found a recency bias for 105 of 168 participants. The primacy-recency parameter was significantly different from one (M = 1.28, SD = 1. 47, CI = [1.06, 1.51], $t(167)$ = 2.51, p = .013), suggesting that for most participants, choices were more heavily influenced by more recent deck draws. The effect size, as measured by Cohen's d, was .19, indicating a negligible effect. We found no side bias with 77 of 169 participants showing a left bias and 92 a right bias. The side bias parameter was not statistically different from zero (M = .07, SD = .53, CI = [-.01, .15], $t(168)$ = 1.74, p = .08). In contrast, we found a positive inverse temperature for 165 of 168 participants. On average, the inverse temperature parameter, which measured reward sensitivity, was significantly greater than zero (M = .02, SD = .02, CI = [.02, Inf], $t(167)$ = 20.48, $p < .0001$), suggesting that participants' responses were systematically attuned to the difference between the expected utility of the deck and the sure-thing offer. The effect size, as measured by Cohen's d, was 1.58, indicating a large effect. Finally, we found a deck bias for 147 of 169 participants. The safe bias parameter was significantly different from zero (M = -.62, SD = .59,

CI = [-.71, -.53], $t(168) = -13.66$, $p < .0001$), suggesting that participants had a response bias for choosing the deck. The effect size, as measured by Cohen's *d*, was 1.05, indicating a large effect.

To illustrate the fit of the Base Cognitive Model, we plotted the average choice curve based on both observed and simulated data (Fig 6). For examples of individual choice curves, see Appendix B.

Fig 6

Average Choice Curve Based on Observed and Simulated Data



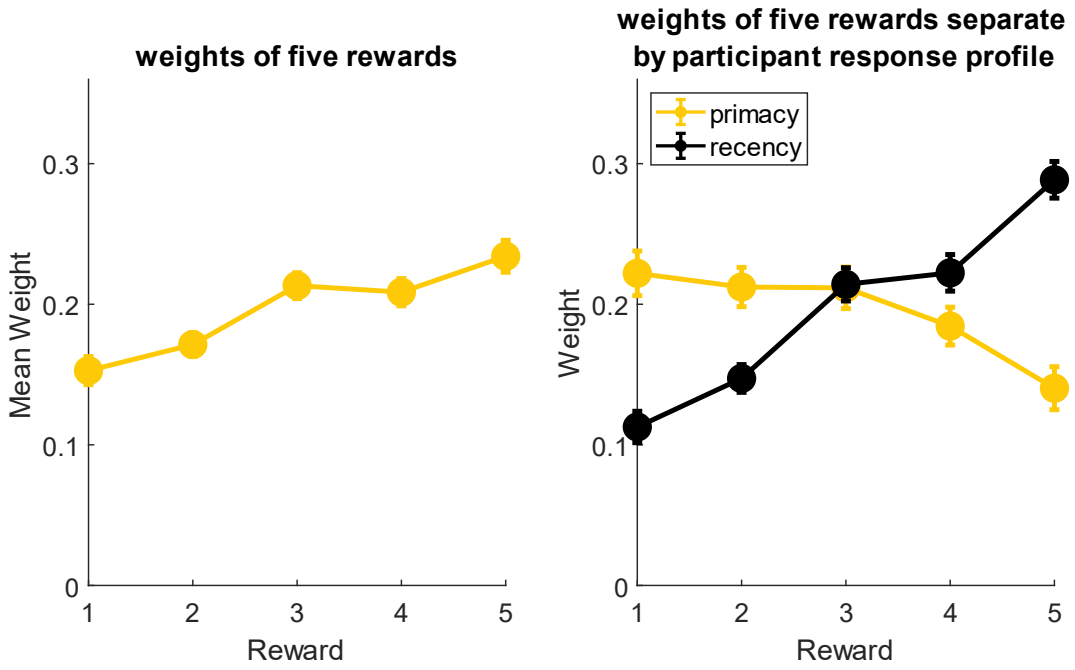
Note. The horizontal dashed line represents random choice between the deck and the sure-thing offer; the vertical dashed line represents the mean reward of the deck being identical to the sure-thing offer.

Exploratory data analysis

The average of the five weights from fitting the Free-Weight Cognitive Model indicated that individuals weighed more recent rewards more heavily than earlier ones. This finding points to an overall recency bias (Fig 7). Specifically, 37% of participants demonstrated a primacy bias and 63% a recency bias.

Fig 7

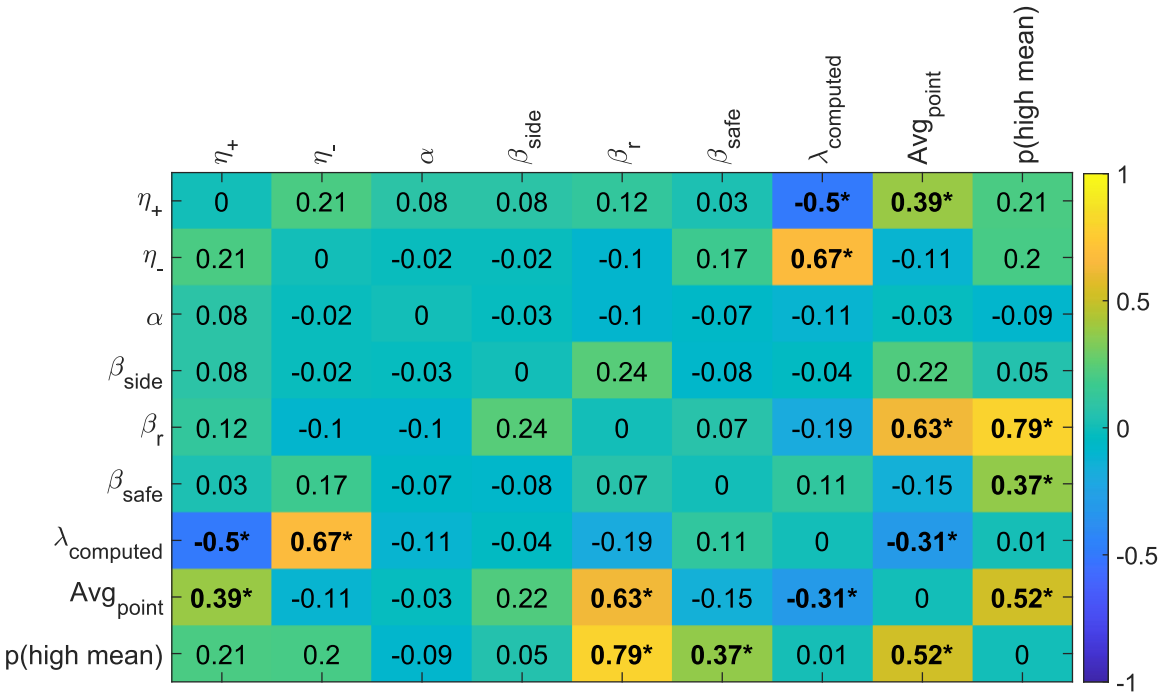
Weights for the Five Rewards Based on the Free-Weight Cognitive Model



Note. (A) Average weights of the five rewards across all participants (B) Average weights of the five rewards for participants demonstrating either a primacy (37%) or a recency (63%) bias.

Fig 8

Intercorrelations Between Individual Differences in Parameter Values, Average Points, and Probability of Choosing the High Mean Option



Note. Spearman correlation coefficients are shown. The p values were adjusted using the Holm correction.

Individual differences in fit values. The distributions of parameter fit values (Fig 4) suggest that individuals use different strategies during decision making. To understand how these inter-individual differences in cognitive components drive decisions, we correlated them with individuals' average points obtained in the FLAG task and their probability of choosing the option with the higher mean (i.e., the higher value between the sure-thing offer and the average of the five examples from the deck). Results showed that the average point a participant received was negatively associated with the computed ratio of loss aversion but positively associated with both curvature for gains and inverse temperature (Fig 8). These findings suggest that in complex decisions such as the FLAG task, making the most profitable decisions might involve reduced diminishing sensitivity to gains and reduced loss aversion, but increased response consistency and gain seeking.

Discussion

Optimal integration of information for adaptive decision making is a crucial skill in everyday life [25]. This task becomes increasingly demanding for children and adolescents [26,27], as well as older adults and individuals with mental illness [1,28]. To better help people with decision deficits, it is paramount to delineate the psychological mechanisms that underpin value integration during decision making [18]. To our knowledge, the present study is the first to use computational modeling techniques to examine how learning processes, such as primacy-recency bias, combine with cognitive biases from Prospect Theory, such as curvature and loss aversion, to shape the value integration stage of decision making.

Specifically, the FLAG task entails repeated interactions with the deck, which requires participants to integrate information across multiple trials. This learning component is often either absent from previous research [for an exception, see 29] or examined with rather limited capacity [5]. For example, studies of experience-based decision making [5] typically restrict each option to just two outcomes per decision, limiting insights into how individuals evaluate complex reward structures and integrate multiple outcomes of varying magnitudes. In contrast, each decision in the FLAG task entails five variable outcomes drawn from a distribution, with an additional outcome if the deck is chosen. This setup encourages participants to actively integrate the five sampled outcomes across trials to form a comprehensive evaluation of the deck's overall utility, a process likely driven by both *sensitivity to outliers (curvature)*, *loss aversion*, and *primacy-recency bias*. In addition, with a fixed set of five outcomes per deck, rewards are not contingent on the choices participants make. This setup allows the FLAG task to control for the exploration-exploitation tradeoff [30], providing more precise examination of how different cognitive biases shape value integration during complex decisions.

Memory plays a crucial role in the value integration stage of decision making [17,18]. By examining how learning processes combine with decision features from Prospect Theory, the FLAG task will shed light upon how age-related changes in learning and memory affect decisions involving gains and losses in aging. Specifically, the sequential presentation of card values in the FLAG task allows us to examine how primacy and recency biases influence decisions. Consistent with the recency bias, we found that most participants based their choices more on recent draws, weighing the outcomes of more recent example cards more heavily when evaluating the deck's overall utility. Although the effect size was negligible (ostensibly due to individual differences in recency bias), these findings highlighted the important role recency bias plays in value integration during decision making [31,32].

Our findings of a concave utility curve for gains and a convex utility curve for losses replicated previous findings in the decision-making literature [33–35] and corroborated the Prospect Theory [4]. Notably, a considerable proportion of participants exhibited near-zero curvature for gains (29%), losses (48%), and both (14%), suggesting that these participants largely ignored the magnitude of the outcomes, focusing instead on the sign (positive or negative) of the outcomes.

Nevertheless, we did not replicate loss aversion, a defining feature of the Prospect Theory [36; but see 37 for the opposite finding]. Our results suggest that loss aversion might not be as robust when combined with other decision features as when it is examined in isolation. Instead, 63% of participants exhibited gain-seeking behavior, the opposite of loss aversion (Fig 5). Although these findings deviate from the assumptions commonly made in modeling decision making under Prospect Theory, they aligned with findings among financial professionals, a

notable proportion of whom tend to emphasize gains and downplay losses. Some researchers argue that this gain-seeking behavior may contribute to financial crisis [38–40].

The absence of loss aversion in our data parallelled findings in several other studies [29,33,35,37,41] and could be attributable to several task characteristics [42]. First, in the FLAG task, participants based their decisions on *experience* with the alternatives under ambiguity (unknown probabilities), without prior knowledge of outcomes [29]. In contrast, in studies demonstrating loss aversion [34], participants based their decisions on explicitly described outcomes, with known probabilities (under risk) [43]. In this regard, our findings aligned with the description-experience gap, in which participants tend to be more risk-seeking for gains than for losses when learning probabilities through experience [44]. Second, our specification of the utility function (Equation 1), in which curvature for gains (η_+) and curvature for losses (η_-) were allowed to take on different values as opposed to assuming a common curvature for gains and losses, also tends to underestimate loss aversion [41]. Finally, as Rieskamp (2008) argued, the lack of loss aversion might be attributable to the large number of trials in the task, in which pairs of gambles with gains, losses, and mixed payoffs are presented randomly, leading participants to pay less attention to losses relative to gains.

Limitations and future directions. Our study focused on typically developing young adults, which may limit the generalizability of these findings. Moving forward, the FLAG task bears potential to advance understanding of decision deficits in aging and clinical populations. For example, older adults exhibit deficits in experience-dependent decision making, and this impairment is exacerbated in social domains, as observed in a recently developed social version of the IGT [28]. Thus, future research might benefit from exploring the different strategies that

young versus older adults might adopt during decision making and quantifying their differences in cognitive biases [10,45]. The FLAG task is especially suitable for this endeavor.

Decision deficits are also a core symptom of depression. Using large-scale panel data, a recent study found that depressive symptoms were unrelated to behavioral measures of risk attitudes, although actual risk-taking behavior clearly suggested differences between depressed vs. mentally well individuals [46]. Given that depression is linked to decreased reward learning [47], the FLAG task may serve as an alternative behavioral measure of risk attitudes (e.g., curvature), incorporating a learning component (e.g., primacy-recency bias) to address the link between depression and risk preference. At present, however, the FLAG task may be too time-consuming to be easily implemented as a routine assessment tool in clinical settings. Specifically, the large number of trials, coupled with the complex reward structures, renders the FLAG a rather long and cognitively demanding task. Although both the average points per game and sensitivity were significantly higher than chance (Fig 2 and Fig 3), suggesting that participants did not perform randomly, the length of the FLAG task may still limit its clinical utility. Therefore, a promising future direction would be to construct and validate a brief version of the FLAG task. In addition, future research should extend the FLAG task to real-world scenarios, such as financial, political, and health decision-making, to investigate how cognitive components interact in those contexts. The applicability of the FLAG task across diverse populations and settings remains an exciting avenue for further exploration.

Research on decision making using the FLAG task will also benefit from considering alternative models of behavior, such as the Range-Frequency Theory [48]. In the context of decision making, the Range-Frequency Theory posits that both the *range* and *frequency* of outcomes influence decisions by shaping the perception of outcomes in relation to their

subjective magnitude, relative position, and frequency of occurrence [49]. The concept of "range" refers to the span of outcomes a person encounters. The range determines the position of the outcomes relative to the highest and lowest outcomes in the set. Consistent with the *range* principle, research on the macaque orbitofrontal cortex (OFC) demonstrates that neurons encoding the subjective value of choices partially adapt to the range of values. This partial adaptation allows for flexibility in responding to changing environments but may compromise decision-making efficiency [50]. In the context of the FLAG task, the Range-Frequency Theory predicts that subjective reward values are influenced by the range of outcomes within a deck, which would, in turn, be influenced by the presence of large gains or losses. This consideration is particularly relevant for future research involving monetary incentives, when the range of gains and losses will be smaller.

To summarize, in this article, we demonstrate the ability of our newly designed FLAG task to identify and isolate the influence of various cognitive biases, including *sensitivity to outliers (curvature)*, *loss aversion*, and *primacy-recency bias*, on decision making. Our study offers first evidence supporting the utility of the FLAG task and its associated data analytic approaches as valuable tools for modeling value integration during decision making under uncertainty. Our initial findings from this research reveal that when faced with multiple outcomes over repeated interactions, humans tend to underweight outliers for both gains and losses, without necessarily weighing losses more heavily than gains. In addition, their value integration across trials is governed by a recency bias. These findings are broadly consistent with Prospect Theory but challenge the assumption of loss aversion. Our work contributes a novel and versatile experimental tool to the existing repertoire in the decision-making literature and invites broader applications to enhance societal and clinical impacts.

Materials and Methods

Experiment

Ethics statement

The study was approved by the Institutional Review Board (IRB) at the University of Central Florida (approval number STUDY00002127). All participants provided written informed consent in accordance with procedures approved by the IRB.

Participants

One hundred and seventy college students at the University of Central Florida (M_{age} = 20.1, SD_{age} = 2.7, 44% males and 56% females) passed data screening criteria (i.e., normal or corrected-to-normal vision and at least 18 years of age) and completed the FLAG task online implemented in jsPsych [51].

Procedure and measures

Over the course of the task, participants completed 100 trials, each involving a single decision between a variable outcome and a sure-thing offer, in the format of a gambling game. During each game (Fig 1), participants first drew five examples from the deck at their own pace (**Sampling phase**). Deck outcomes centered around an average score, which differed across games and could either be positive or negative (e.g., +250 to -250 points). Then, they chose between drawing another card from the deck and the sure-thing offer (**Choice phase**). During the choice phase, the two options were presented side by side, the location of each being counterbalanced across trials. Each option varied independently and could yield a positive, negative, or zero payout. After selecting either the deck or the sure-thing offer, the value of the chosen card was revealed (**Feedback phase**). Unlike the IGT, where half of the decks include large losses (e.g., -1250 points), the FLAG task symmetrically varies both the magnitude and

frequency of gains in addition to losses, resulting in an equal number (19) of trials with either large gains (e.g., 1310 points) or losses (e.g., -1300 points). Of the one hundred games, thirty-six included all gain trials, thirty-nine all loss trials, and twenty-five a mixture of both gains and losses. Games were presented in random order using the "randomize_order" option in jsPsych [51]. Code to run the task is available on https://github.com/swan232/FLAG. The five example draws within each game were presented in a fixed order. We measured both participants' choices and their response times, but we focused on their choices as the dependent variable to model decisions using Prospect Theory-inspired computational cognitive models. Task completion took about twenty-five minutes.

Analyses

We applied computational cognitive models to examine how experimental manipulations interact with cognitive components to account for behavior in the FLAG task. For all hypothesis testing conducted in this study, a significance level of $\alpha = .05$ was used. All p values were calculated for two tails unless otherwise specified.

Base Cognitive Model

Research demonstrates that in decision making, individuals are sensitive to the amount of both gains and losses and weigh losses more heavily than gains of the same magnitude [4,14]. In addition, when a person evaluates a choice option, different values of gains and losses are integrated into an overall subjective value, often known as the "utility" [15,16]. Furthermore, individuals are averse to large losses, including in social domains [52]. Nevertheless, high-frequency gains can trump large losses, evident in a persistent preference among individuals for choosing deck B in the IGT, where high-frequency gains play a more dominant role in driving decisions than do high-intensity losses [13]. Finally, the primacy and recency biases of recall

memory [21] also influence decision making [19,20]. Given that the FLAG task presents card values sequentially, we anticipated that primacy and recency biases would influence the differential weighting of card values during the process of value integration.

Based on these findings, we developed a Base Cognitive Model, which comprises six free parameters (Table 1) that capture the different cognitive processes possibly underlying decision making and that can be isolated in the FLAG task.

Table 1

Cognitive Model Parameters

Parameter	Symbol	Range
Curvature for gains	η_+	[0, +∞]
Curvature for losses	η_-	[0, +∞]
Primacy-recency bias	α	[0, +∞]
Side bias	β_{side}	[-∞, +∞]
Inverse temperature	β_r	[-∞, +∞]
Safe bias	β_{safe}	[-∞, +∞]

Our model assumes that people make their decision by comparing the relative utilities of the deck and the sure-thing offer such that they are more likely to choose the option that has the higher expected utility. For exposition purposes, it is useful to think of this model as comprising four steps – although we do not propose that people perform this calculation in such a strict stepwise manner.

Step 1 – Utility transformation. First, we assume that rewards are transformed into utilities – the subjective value that participants give to a particular number of points [4]. Following Abdellaoui et al. [53] and Erev et al. [29], we assume the following utility function

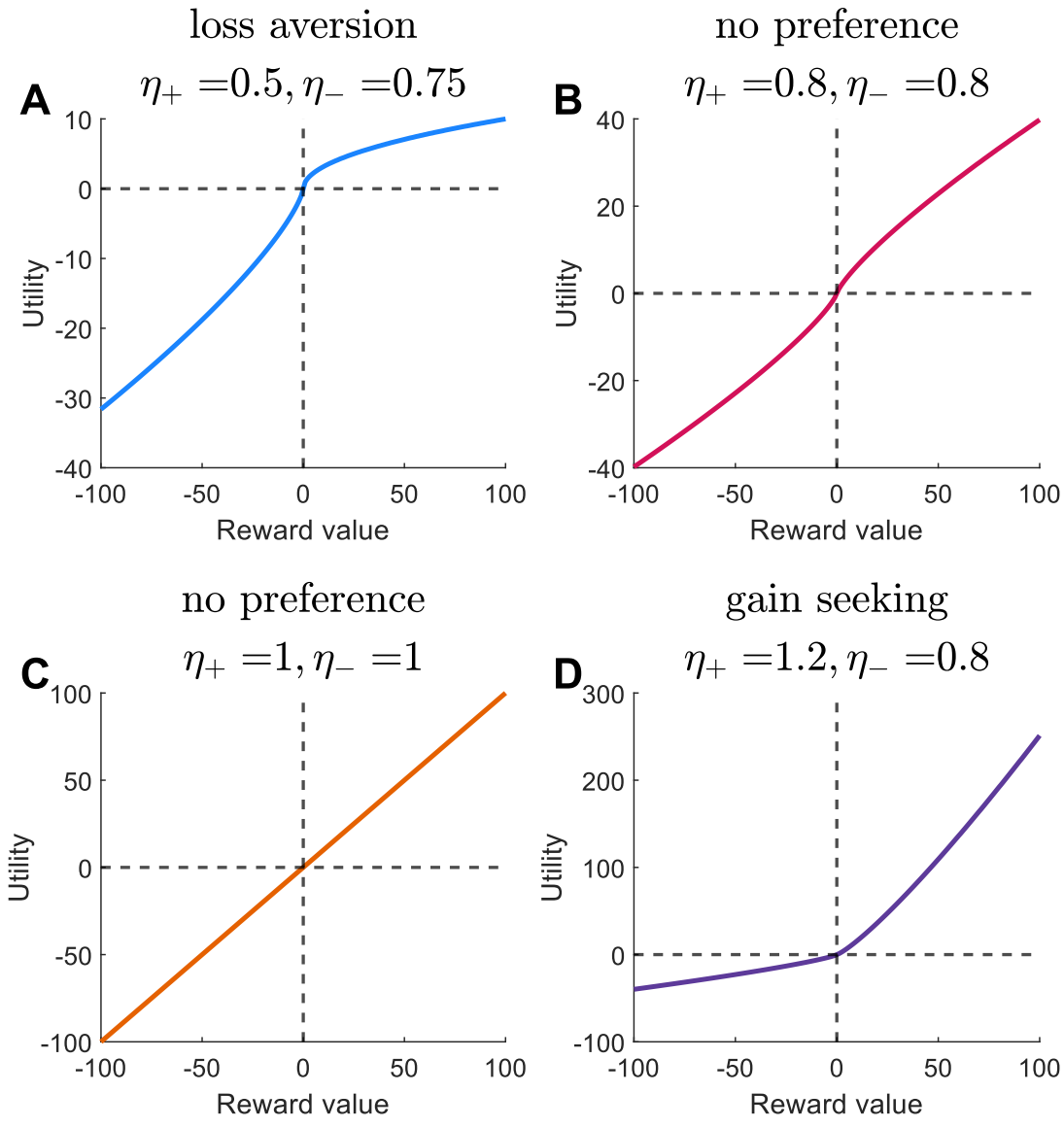
$U(r) = \begin{cases} r^{\eta_+}, & r \geq 0 \\ -\lvert r \rvert^{\eta_-}, & r < 0 \end{cases}$	Equation 1

where η_+ represents the curvature of the utility function for gains and η_- represents the curvature of the utility function for losses. In the standard version of Prospect Theory, the utility curve is concave for gains ($\eta_+ < 1$), convex for losses ($\eta_- < 1$) and with losses weighed more strongly than gains ($\eta_- > \eta_+$). In our formulation we allow the curvature parameters to take on any positive value, with the actual value determined by the model fit.

The curvature parameters dictate how people handle outliers. When $\eta_\pm < 1$ the model underweights outliers, with smaller curvatures leading to less and less difference between the utility of outliers and small magnitude rewards. In the extreme case, when $\eta_\pm = 0$, the absolute value of the reward is ignored completely, and the utility of a reward is simply given by its sign. When $\eta_\pm > 1$ the model overweights outliers, with larger curvatures leading to more and more of a difference between the utility of outliers and small magnitude rewards. Finally, when $\eta_\pm = 1$, the utility is equal to the reward and the model weights outliers "correctly" (Fig 9).

Fig 9

Utility as a Function of Both Curvature for Gains (η_+) and Curvature for Losses (η_-)



Note: Utility curves with η+ and η− that are allowed to freely vary: (A) loss aversion under Prospect Theory with $\eta_+ = .5$ and $\eta_- = .75$ ($\eta_+ < \eta_-$); (B) diminishing sensitivity to both gains and losses and no preference for loss with η+ = η− = .8; (C) linear perception of gains and losses and no preference for loss with η+ = η− = 1; (D) increasing sensitivity to gains, diminishing sensitivity to losses, exhibiting gain seeking behavior with $\eta_+ = 1.2$, $\eta_- = .8$ ($\eta_+ > \eta_-$). The horizontal dashed line represents randomly choosing between the deck and the sure-thing offer,

and the vertical dashed line represents the mean reward of the deck being identical to the sure-thing offer.

Step 2 – Computing the utility of the deck. To compute the expected utility of the deck, the model computes a weighted average of the utilities of the individual draws as follows:

$$U_{deck} = \sum_{i=1}^{5} w_i U(r_i)$$	2

where r_i denotes the ith reward, $U(r_i)$ is the utility of the ith reward computed via Equation 1, and w_i denotes the weight given to reward i and set such that $\sum_i w_i = 1$.

In the most general form of the model, the weights are assumed to be free parameters (apart from the constraint they sum up to 1) allowing for arbitrary patterns of weighting over time. However, this comes at the cost of four free parameters.

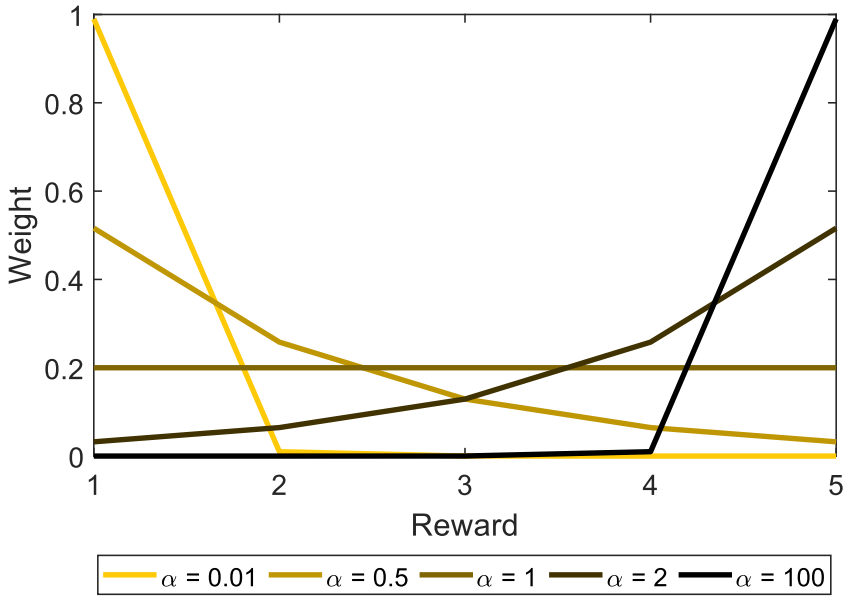
An alternate one-parameter version of the weights, writes the weights as

$$w_i = \frac{\alpha^i}{\sum_{j=1}^{5} \alpha^j} = \frac{\alpha^{i-1}(1-\alpha)}{1-\alpha^5}$$	3

where α controls the shape of the weights. Because the shape of the weights is controlled by just one parameter, this version of the model only allows for certain shapes of the weights (Fig 10). When $\alpha < 1$ early rewards are weighed highest, leading to a primacy bias in which the first rewards are most important in determining the utility of the deck. When $\alpha = 0$, all rewards are weighted equally, leading to the utility of the deck simply being the average of all five utilities. When $\alpha > 1$ the last rewards are weighed highest, leading to a recency bias in which the last rewards are most important in determining the utility of the deck.

Fig 10

Weights For the Five Rewards as A Function of Primacy-Recency Parameter



Step 3 – Converting the utility of the deck to an equivalent reward. In this step, we transform the utility of the deck back into an equivalent reward value. This step is not required for the model to function but makes it easier to compare parameters between participants, as the inverse temperature parameters (Step 4) will now have units of inverse points for all participants instead of having units of inverse utility which varies depending on η_+ and η_-. To compute the equivalent reward value, we simply invert the utility function as follows.

$$R_{deck} = \begin{cases} U_{deck}^{1/\eta_+}, & U_{deck} \geq 0 \\ -\lvert U_{deck} \rvert^{1/\eta_-}, & U_{deck} < 0 \end{cases},$$	4

Step 4 – Decision Rule. Finally, the model makes a decision by comparing the equivalent value of the deck to the value of the sure-thing offer, choosing the deck with probability:

$$p_{deck} = \frac{1}{1 + \exp\left(\beta_{safe} + \beta_{side} s + \beta_r (R_{offer} - R_{deck})\right)}$$	5

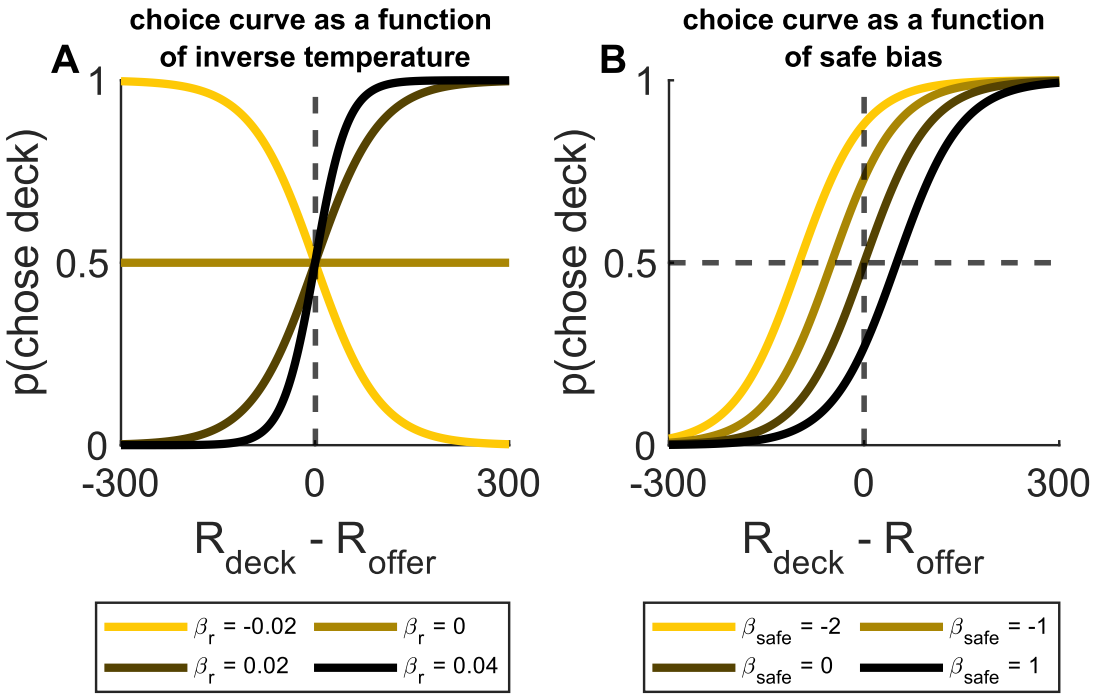
Alternatively, the probability of choosing the left option is given by

$$p_{left} = 1 - p_{right} = \frac{1}{1 + \exp\left(\beta_{side} + (\beta_{safe} + \beta_r (R_{offer} - R_{deck}))s\right)}$$	6

where the experiment parameters are: s denoting the side on which the deck is ($s = +1$ for left, $s = -1$ for right) and R_{offer} the value of the sure-thing offer. The free parameters of the decision rule are: β_{side} denoting the bias towards choosing right, β_r denoting the weight given to the values in determining the decision (i.e., inverse temperature), and β_{safe} denoting the bias towards choosing the sure-thing offer.

Fig 11

Choice Curve for Difference Values ($R_{deck} - R_{offer}$)



Note: (A) choice curve for different β_r given $\beta_{safe} = 0$; (B) choice curve for different β_{safe} given $\beta_r = 0.02$. The horizontal dashed line represents randomly choosing between the deck and the sure-thing offer, and the vertical dashed line represents the expected utilities of the deck and the sure-thing offer being identical.

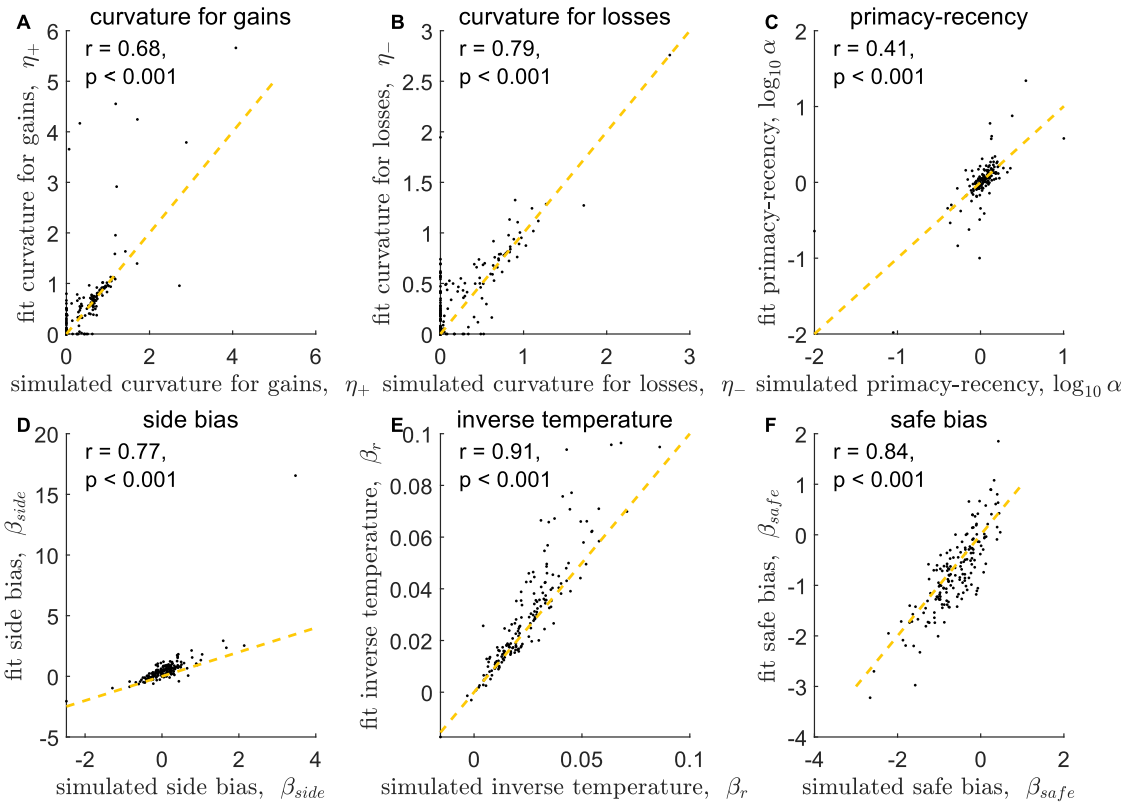
To illustrate how β_r and β_{safe} individually influence decisions, we plotted the probability of choosing the deck as a function of $R_{deck} - R_{offer}$. As shown in Fig 11A, as the differences between the deck and the sure-thing offer values increase, the probability of choosing the deck increases, only if β_r is positive. The greater the magnitude of β_r, the steeper the slope of the choice curve. That is, the sign of β_r determines whether the decision is consistent (+) or inconsistent (-) with the expected utility differences between the sure-thing offer and the deck, and the magnitude of $\beta_r$determines how strongly the decision is driven by the utility difference.

In addition, as shown in Fig 11B, for a given β_r, β_{safe} shifts the choice curve leftward when it is negative and rightward when positive.

We fit these parameters individually to each participant using a maximum likelihood procedure. Data and MATLAB code to reproduce all figures in this paper are available on GitHub at https://github.com/swan232/FLAG_modeling

Fig 12

Parameter Recovery Plot for the Base Cognitive Model



A parameter recovery plot (Fig 12) indicated that the parameter estimation procedure successfully recovered the true values used to generate the simulated data, producing precise estimates of the model parameters.

Free-Weight Cognitive Model

From the base model described above, we removed the primacy-recency parameter to allow weights associated with the five rewards to freely vary. Each model was separately fitted to each participant using the fmincon function in MATLAB.

Data availability statement

Code to run the task is available on https://github.com/swan232/FLAG. Data and MATLAB code to reproduce all figures in this paper are available on GitHub at https://github.com/swan232/FLAG_modeling

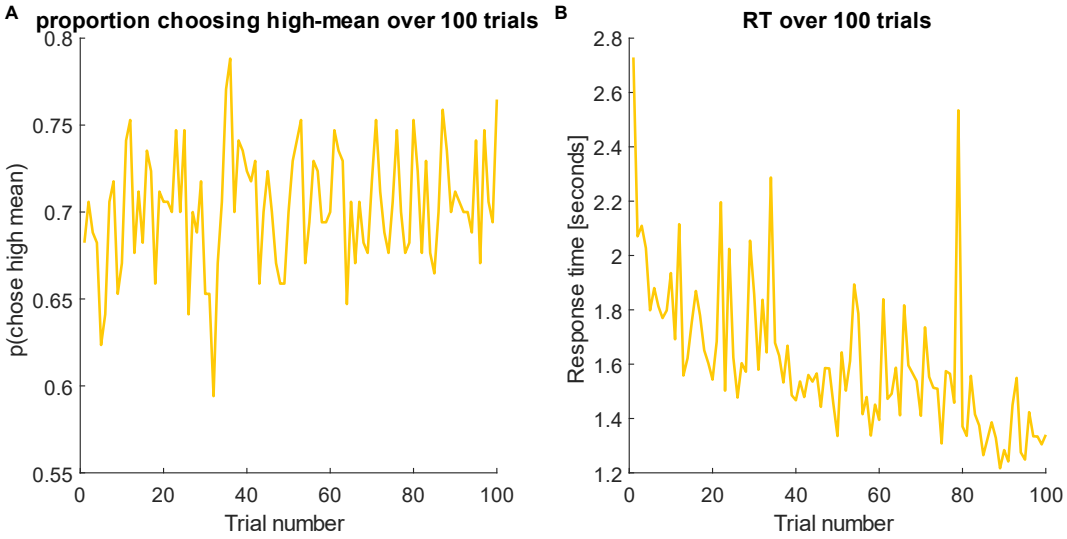
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Competing interests

The authors declare none.

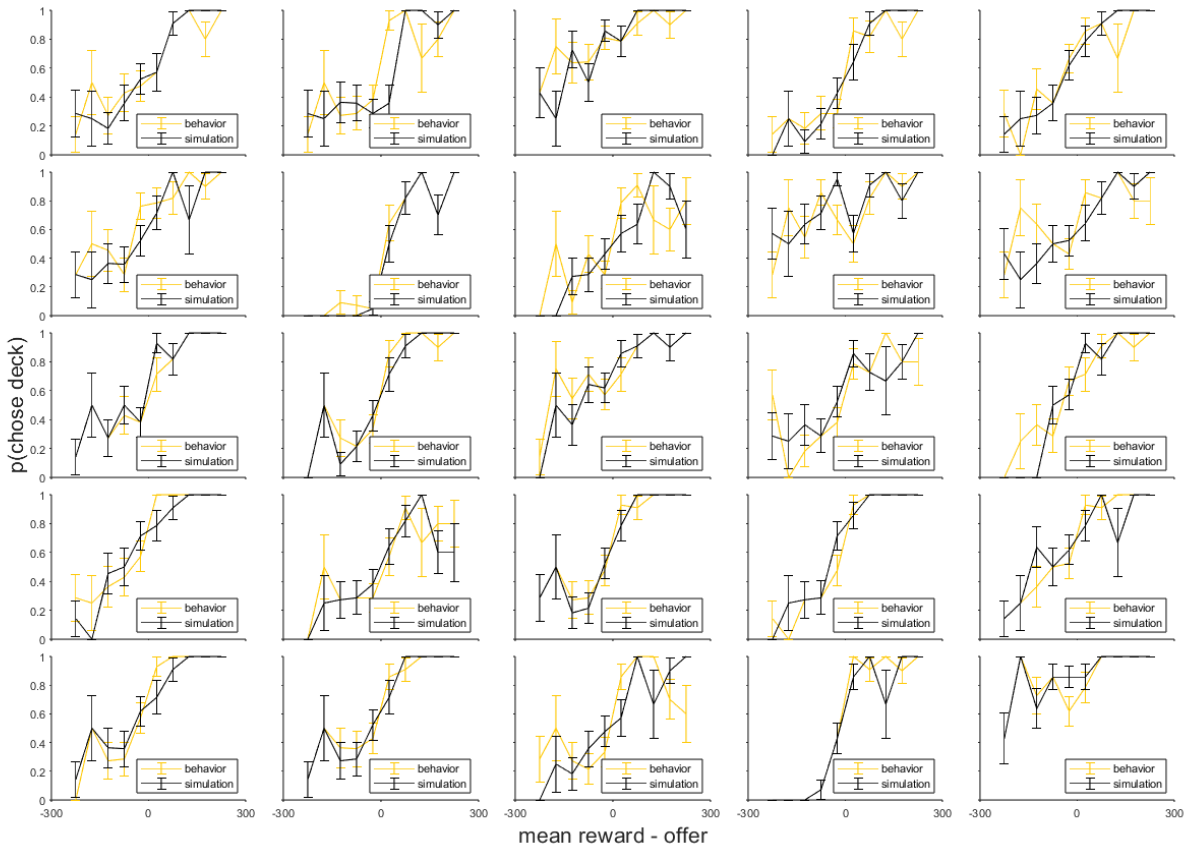
Appendix A



(A) Proportion of participants choosing the high-mean-reward option over 100 trials; (B) Response time for choices over 100 trials

Appendix B

Sample Individual Choice Curves Based on Observed and Simulated Data for 25 Participants



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