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How Prior Experience Shapes Decision-Making Under Uncertainty: Insights from the Iowa Gambling Task

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Abstract

Experience from repeated analogous situations can bias subsequent decision-making, yet it remains unclear whether such effects arise from prior experience itself or the valence of that experience. We investigated whether prior gain or loss modulates subsequent uncertain decisions compared to a no-experience control. Participants completed a manipulated Iowa Gambling Task (M-IGT), inducing predetermined gain or loss, followed by the standard IGT. Prior experience group showed altered exploratory behavior in the early phase, with the loss group exhibiting early risk aversion. Behavioral differences across control and prior experience groups converged later in the task. The $PVL-\Delta$ model revealed that prior experience initially reduced outcome sensitivity. In the later blocks, the gain group showed reduced learning rate and higher outcome sensitivity, indicating strategy stabilization. Prior loss was associated with higher choice consistency across all blocks. These findings suggest that prior experience transiently biases early exploration, while valence shapes decision consistency and learning flexibility.

Keywords: Iowa Gambling Task; prior experience; decision-making under uncertainty; exploratory behavior; outcome sensitivity; choice consistency; $PVL-\Delta$; framing effect

Introduction

Prior experiences play a critical role in shaping how individuals approach similar situations in the future. Studies have shown that failures or successes in previous tasks influence performance in subsequent similar tasks (Geraci et al., 2013; Lemaire & Brun, 2018). However, much of this work has focused on skill-based domains. In contrast, many real-world decisions are made under uncertainty, where outcomes are probabilistic and involve both potential rewards and losses. In such contexts, individuals may experience gains or setbacks, but it remains unclear whether subsequent decision-making is shaped primarily by the valence of prior outcomes (gain vs. loss framing) or by the mere presence of prior experience itself, irrespective of valence. Disentangling these possibilities is essential for understanding how early experiences bias decision-making under risk.

Franken et al. (2006) reported that prior gain and loss experiences modulated subsequent Iowa Gambling Task (IGT) performance in opposite directions, consistent with Prospect Theory predictions (Kahneman & Tversky, 1979), which predicts risk aversion under gains and risk-seeking under losses. However, Rosi et al. (2016) failed to replicate these valence-based effects, raising questions about the robustness of framing influences. Critically, neither Franken et al. (2006) nor Rosi et al. (2016) included a no-prior-experience control group, without which it is not possible to determine whether gain and loss groups deviated in opposite directions relative to neutrality. Prior exposure to the task itself, independent of valence, may have been sufficient to influence subsequent decisions. Thus, it remains unclear whether and how the valence of a prior experience shapes decision-making under uncertainty.

Moreover, outcome valence may not be the only mechanism through which prior experience influences decision-making. Alternative accounts emphasize the role of attentional engagement and cognitive control, particularly following aversive outcomes. The Loss Attention Framework proposes that losses selectively heighten attention to task-relevant information, leading to more cautious or structured decision strategies (Yechiam & Hochman, 2013). Importantly, without a neutral baseline and without examining underlying cognitive processes, the existing literature cannot adjudicate between valence-based framing effects and experience-driven learning constraints.

Behavioral results alone do not provide direct insight into the cognitive mechanisms underlying these effects. Computational modeling enables these mechanisms to be disentangled by separately estimating learning, valuation, exploration, and loss aversion processes beyond what can be inferred from overt behavior alone.

To address these gaps, we tested whether decision-making in a subsequent task under uncertainty is shaped by prior experience of the analogous task itself or by the valence (gain/loss) of that prior experience. We applied the $PVL-\Delta$ model of the IGT to our behavioral data as a mechanistic tool to dissociate the effects of prior experience on decision-making under uncertainty.

Materials and methods

Participants

A total of 166 young adults (19–30 years; 130 male, 36 female) were recruited from the undergraduate and graduate population at the International Institute of Information Technology, Hyderabad (IIIT-H). Gender proportions were evenly distributed across experimental conditions. Participants had no history of psychiatric conditions, no gambling problems, and no previous exposure to IGT or similar tasks. The study protocol was approved by the Institutional Review Board (IRB) of IIIT-H. All participants provided informed consent prior

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to the commencement of the experiment and received course credits as compensation for their participation.

A priori power analysis was conducted using G*Power (Faul et al., 2007) and was based on Rosi et al. (2016) study. Assuming a moderate effect size ($f = 0.25$), $\alpha = 0.05$, and desired power of 0.95 for a mixed ANOVA, the estimated required sample size was 56 participants in each condition – loss and gain.

Experimental Tasks

Iowa Gambling Task: The Iowa Gambling Task (IGT) consists of 100 trials (20 trials x 5 blocks). Participants must choose one card at a time from one of the 4 decks (A, B, C, D). Each deck has its own schedule of gains and losses which is used to measure participants' approach to risk taking. We followed the original IGT structure by Bechara et al. (1994) (100 trials; four decks differing in gain–loss schedules; see Table 1). In the first block, participants typically explore all the decks. By Blocks 2 and 3, participants try strategies and, generally, healthy participants start selecting more advantageous decks (C & D) (Dunn et al., 2006). Accordingly, participants are expected to progressively gravitate towards advantageous decks as the task progresses (Bechara et al., 1997).

In our study, the participants were instructed to make as much money as possible and employ their own strategies. They were not informed about the contingencies or the number of trials. The performance of participants was divided into 5 blocks of 20 trials each ($5 \times 20 = 100$ trials). Performance was scored as follows: Number of cards selected from the advantageous decks minus the number of cards selected from the disadvantageous decks $[(C+D)-(A+B)]$. This is known as Beneficial Deck Choices [1] and was computed for each block. Scores above zero indicated that the participants were selecting more advantageous decks whereas scores below zero indicated selection of disadvantageous decks (Bechara et al., 1994).

Manipulated Iowa Gambling Task (M-IGT): To introduce a prior-experience of gain or loss, the IGT was modified to give the participants a subjective experience of gain or loss by controlling the outcome (gain/loss), without any control on deck outcomes.

The M-IGT consisted of 40 trials in which four decks of cards (A, B, C, D) were presented on a computer screen, and participants had to select one card at a time, as in the original IGT. However, each card yielded a predetermined gain or loss contingency, irrespective of the deck choices. The deck outcomes in M-IGT gradually and cumulatively led to either loss or gain after 40 trials.

Participants started the game with no endowment (0 units). In the gain version of M-IGT, participants randomly ended with a gain of approximately 2000 units (1800, 2000, or 2200) while in the loss version of M-IGT participants randomly ended with a loss of approximately 2000 units (1800, 2000, or 2200). These amounts were intended to create an experience of loss or gain. Rosi et al. (2016) had similar end amounts to ours, in Euros, in the M-IGT whereas Franken et al. (2006) had different gain (€4) and loss (€10) amounts.

Based on pilot testing and prior work (Rosi et al., 2016), the M-IGT consisted of 40 trials to minimize the detection of manipulation.

[1] When selecting decks, a positive mean indicates a preference for beneficial decks, while a negative mean indicates a preference for disadvantageous ones.

Table 1: Magnitude and frequency of gain and loss across IGT and M-IGT variants

Variable	Deck A	Deck B	Deck C	Deck D
Iowa Gambling Task (IGT)				
Mean gain	+100	+100	+50	+50
Mean loss	−125	−125	−25	−25
Loss probability	5 every 10 selections	1 every 10 selections	5 every 10 selections	1 every 10 selections
Expected value	−25	−25	+25	+25
Loss-Frame M-IGT (Loss Manipulation)				
Mean gain	+50	+50	+50	+50
Mean loss	−100	−100	−100	−100
Loss probability	5 every 10 selections	5 every 10 selections	5 every 10 selections	5 every 10 selections
Expected value	−50	−50	−50	−50
Gain-Frame M-IGT (Gain Manipulation)				
Mean gain	+150	+150	+150	+150
Mean loss	−100	−100	−100	−100
Loss probability	5 every 10 selections	5 every 10 selections	5 every 10 selections	5 every 10 selections
Expected value	+50	+50	+50	+50

Questionnaires: Participants completed the Patient Health Questionnaire-9 (PHQ-9) for depression screening (Kroenke et al., 2001) and the State-Trait Anxiety Inventory (STAI) for anxiety screening (Spielberger, 1982).

Procedure

Participants were seated in a quiet room and completed the tasks on a laptop. They first performed a 40-trial M-IGT, during which either manipulated gain or manipulated loss outcomes were randomly assigned. Following this, these participants completed the standard IGT. The control group performed only the standard IGT and did not complete the M-IGT, serving as a comparison group without prior task experience. Experiment structure is illustrated in Figure 1. The experiment was programmed and executed using OpenSesame (version 4.0). All participants were debriefed at the end of the experiment.

Prospect Valence Learning ($PVL-\Delta$) Modeling of Decision Behavior

To decompose the latent cognitive processes underlying decision-making, we applied the Prospect Valence Learning (PVL-Δ) model to the IGT data. $PVL-\Delta$ model uses Prospect

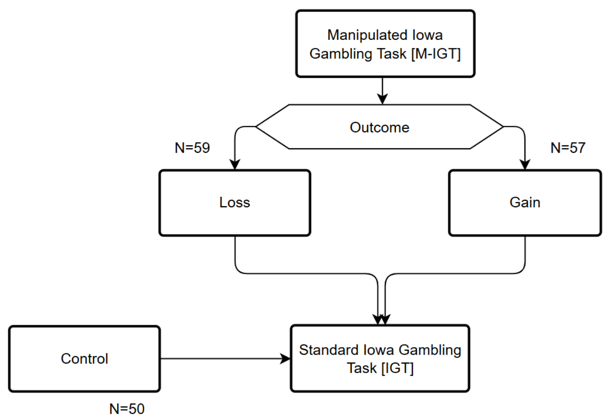

Figure 1: Experiment structure from Phase 1 to Phase 2. Manipulated - Iowa Gambling Task (M-IGT), original Iowa Gambling Task (O-IGT). The Control group received no prior exposures and only performed the O-IGT.

Theory's utility function (modeling sensitivity to gains/losses) with a Delta learning rule to update deck expectancies. It estimates four specific parameters (Ahn et al., 2008):

- **Outcome sensitivity (α):** Determines the curvature of the utility function, representing a participant's sensitivity to the magnitude of gains and losses.
- **Loss Aversion (λ):** Weights the subjective impact of losses relative to gains.
- **Learning Rate (A):** Controls the speed of expectancy updates, determining how much recent outcomes influence future deck choices compared to past experiences.
- **Response Consistency (c):** Reflects the degree to which a participant consistently exploits the deck with the highest expected value versus making exploratory choices.

Parameters were estimated using Maximum Likelihood Estimation (MLE), with constraints applied according to established ranges (Ahn et al., 2008). To capture potential temporal dynamics in strategy use, model fitting was conducted for the full task as well as separately for early (Blocks 1-2) and late (Blocks 3-5) phases. This approach allowed us to examine whether prior-experience influenced early valuation or early learning processes, independent of long-term task performance. Model fit was evaluated using AIC and BIC. For the standard IGT across all groups, Mean AIC = 266.30 and Mean BIC = 276.73 (success rate = 100%); for the M-IGT (gain and loss groups), Mean AIC = 114.20 and Mean BIC = 120.96 (success rate = 98.3%), indicating adequate model recovery across both tasks.

Results

Data preprocessing and statistical analyses were conducted using Python and JAMOVI (version 2.6.44). No participants were eliminated from the analysis based on screening questionnaires.

Effect of prior-experience on beneficial deck selections in the IGT, adding a control group

To assess whether prior-experience influenced decision-making, we compared gain, loss, and control groups (Fig. 1). We used a mixed ANOVA with Group (gain, loss, control) as between-subject factor and Block (1-5) as within-subject factor. We observed an effect of Block (1-5) ($F(4, 648) = 25.39$, $p < .001$, $\eta_p^2 = .14$) where choice of beneficial decks increased linearly as participant progressed from Block 1-5 in all groups, Figure 2A.

We observed a main effect of group (gain, loss, control) on beneficial deck choices across Blocks (1-5) ($F(8, 648) = 2.50$, $p = .011$, $\eta_p^2 = .03$). We focused on post-hoc comparisons only for Blocks 1, 2, and 3 based on previous studies which showed that participants develop preferences by Block 2 and 3 (Bechara et al., 1994; Maia & McClelland, 2004). In Block 1, one-way ANOVA with group (gain, loss, control) on the beneficial choices made in Block 1 revealed a main effect of group ($F(2, 163) = 17.5, p < .001, \eta_p^2 = 0.17$). Tukey's post-hoc analysis showed that beneficial deck choices were lower in the control group compared to gain group ($p < .001$) and loss group ($p < .001$). There was no difference between beneficial decks chosen between gain and loss groups ($p = .96$). This suggests that prior-experience changed exploratory behavior in Block 1 in the gain and loss group compared to the control group (Figure 2B). In Block 2, one-way ANOVA examining group differences on beneficial choices showed a main effect of group ($F(2, 162) = 7.32$, $p < .001$, $\eta_p^2 = .083$). Tukey's post-hoc showed that the loss group had chosen more beneficial decks than the gain group ($p = .012$) and control group ($p = .001$). There was no difference in beneficial decks chosen between gain and control groups ($p = 0.71$). Contrary to the findings of Franken et al. (2006), our findings showed that the loss group chose more beneficial decks than the gain group (Figure 2B). In Block 3,a one-way ANOVA examining the effect of group on beneficial choices showed no difference between the three groups ($F(2, 163) = 1.85$, $p = 0.16$). The differential effect of prior-experience on deck choices did not persist beyond Block 2.

Cognitive processes underlying task performance

To characterize latent decision-making processes underlying task performance, we fitted a Prospect Valence Learning model with a delta learning rule ($PVL - \Delta$) to participants' IGT data. Separate ANOVAs were conducted with group (gain, loss, control) as the between-subjects factor on each model parameter [A (learning rate), α (outcome sensitivity), λ (loss aversion), c (choice consistency)]. Analyses were performed for overall performance across all blocks as well as separately for early (Blocks 1&2) and late (Blocks 3-5) task phases. For non-significant comparisons of theoretical interest, we supplement frequentist p-values with Bayes factors (BF_{10}) computed via Bayesian ANOVA in JASP (JASP Team, 2024), using a default Cauchy prior on effect size ($r = 1/\sqrt{2}$) (Rouder et al., 2012).

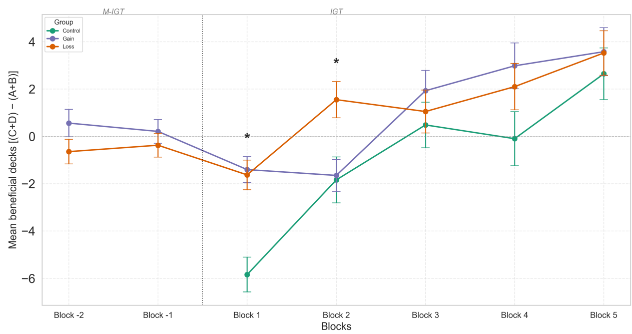

Figure 2: Frequency of beneficial deck selections across M-IGT and IGT blocks. Mean frequency of advantageous (C+D) minus disadvantageous (A+B) choices across 2 M-IGT blocks and 5 IGT blocks, as a function of prior gain, prior loss, and control conditions. Bars indicate standard error of the mean.

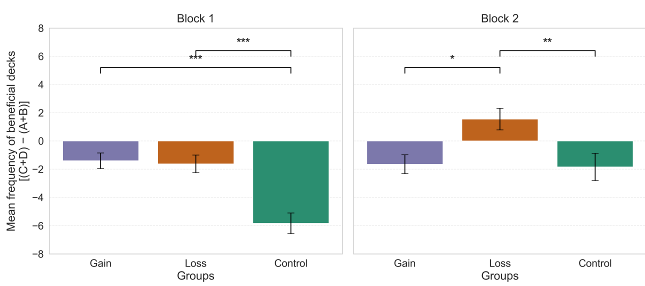

Figure 3: Focused view of beneficial deck choices in Blocks 1 and 2. This visualization isolates early-stage performance to illustrate differences between Prior Gain, Prior Loss, and Control groups in advantageous selections [(C + D) - (A + B)]. Bars indicate standard error of the mean.

$PVL-\Delta$ Parameters over all blocks: When the model was fit to data from all blocks, no significant group differences were observed for learning rate (A), $F(2,163) = 0.92$, $p = .400$, or outcome sensitivity (α), $F(2,163) = 0.74$, $p = .480$. Loss aversion (λ) showed a non-significant effect, $F(2,163) = 2.38$, $p = .096$; Bayesian analysis yielded $BF_{10} = 0.459$, indicating weak evidence in favour of the null and suggesting the observed trend does not reflect a reliable group difference in loss aversion. In contrast, a significant effect of condition was observed for choice consistency (c), $F(2,163) = 3.12$, $p = .047$, $\eta_p^2 = .037$. Post-hoc Tukey comparisons indicated higher choice consistency in the loss group compared to the control group ($p = .036$), suggesting more deterministic decision-making under prior loss framing.

Together, these results suggest that while the overall trajectory of learning and outcome valuation was broadly similar across groups, prior loss experience produced a more rigid, consistent decision policy across the full task, a pattern consistent with the Loss Attention Framework (Yechiam & Hochman, 2013).

$PVL-\Delta$ Parameters in Early Phase (Blocks 1–2): In early blocks, learning rate (A) did not differ by condition, $F(2,163) = 0.735$, $p = .481$. A significant group effect was observed for outcome sensitivity (α), $F(2,163) = 5.27$, $p = .006$, $\eta_p^2 = .061$. Post-hoc comparisons revealed lower sensitivity in both the gain ($p = .009$) and loss ($p = .021$) groups relative to the control group, with no difference between gain and loss groups ($p = .949$). No significant effects were found for loss aversion (λ), $F(2,163) = 1.55$, $p = .215$, or choice consistency (c), $F(2,163) = 2.28$, $p = .105$. Lower outcome sensitivity in both prior-experience groups indicates a blunted responsiveness to payoff magnitudes during early task exploration. This pattern is consistent with participants relying on cached value representations formed during the M-IGT rather than dynamically updating to new IGT outcomes which indicates a transient shift toward model-free behaviour (Daw et al., 2005).

$PVL-\Delta$ Parameters in Late Phase (Blocks 3–5): When the model was fit to the late phase, a significant effect of group emerged for learning rate (A), $F(2,163) = 3.79$, $p = .024$, $\eta_p^2 = .044$. Post-hoc tests indicated that the gain condition showed a significantly lower learning rate than the control condition ($p = .019$), with no other significant pairwise differences. Outcome sensitivity (α) also differed by group, $F(2,163) = 3.60$, $p = .029$, $\eta_p^2 = .042$. Post-hoc analyses showed higher sensitivity in the gain group relative to the control group ($p = .040$). The loss group showed a numerically similar pattern ($p = .069$); Bayesian post-hoc analysis of the loss–control comparison yielded $BF_{10,U} = 2.503$, providing anecdotal evidence for a group difference in late-phase outcome sensitivity, consistent with the overall model effect. No significant effects were observed for loss aversion (λ), $F(2,163) = 0.509$, $p = .602$, or choice consistency (c), $F(2,163) = 0.273$, $p = .761$. In the $PVL-\Delta$ framework, the combination of a reduced learning rate and elevated outcome sensitivity observed in the gain group during later blocks indicates strategy stabilisation: participants had become attuned to payoff magnitudes but were less likely to revise their internal model based on individual trial outcomes. This suggests that prior gain experience accelerated the crystallisation of a stable decision policy.

$PVL-\Delta$ Parameters in M-IGT and Condition differences prior to the IGT: To examine whether gain and loss groups differed in their cognitive profiles during the M-IGT itself, we fitted the $PVL-\Delta$ model to M-IGT choice data and compared parameters between conditions. Since M-IGT outcomes were predetermined irrespective of deck choices, parameters reflecting outcome-driven learning (α, A) should be interpreted cautiously; choice consistency (c), which captures deck preference behavior independent of outcome contingency, is the most interpretable parameter in this context. A one-way ANOVA revealed a significant effect of condition on choice consistency (c), $F(1,114) = 6.46$, $p = .012$, $\eta_p^2 = .054$, with the gain group showing higher consistency (M = 2.46, SD = 2.30) than the loss group (M = 1.41, SD = 2.12), indicating more deterministic deck preferences during M-IGT under gain framing. To further examine whether the condition-level differences in α observed in early IGT blocks were already present during M-IGT, a linear mixed-effects model (LMM) was fit with α as the outcome, stage (M-IGT vs. early IGT Blocks 1–2), condition (gain vs. loss), and λ as fixed effects, and participant as a random effect. Condition significantly predicted α across both stages (β = 0.279, p < .001), while the stage transition itself was not significant (β = −0.121, p = .109), indicating that the between-group difference in outcome sensitivity was stable from M-IGT into early IGT rather than emerging anew upon task transition.

Discussion

This study examined how prior-experience with gain or loss outcome influenced subsequent decision-making under uncertainty by explicitly contrasting prior gain, prior loss, and no-experience conditions. We replicated the study by Franken et al. (2006), with the critical addition of a no-experience control group, to understand whether a prior-experience itself or the valence of a prior outcome shapes subsequent decision-making under uncertainty. Our results showed that participants who had a prior-experience- irrespective of valence shifted early exploratory behavior toward the advantageous decks (C+D) in Block 1 of the original IGT (Figure 2), compared to the control group. However, this trend of choosing advantageous decks persisted in Block 2 only for the loss group (Figure 2B), suggesting risk-averse decisions. By Block 3, all groups converged. Computational modeling using the $PVL-\Delta$ revealed that the mechanisms underlying these behavioral patterns diverged across groups in ways that were not apparent from behavior alone.

Rosi et al. (2016) reported no influence of prior-experience while Franken et al. (2006) showed that prior losses and gains influenced performance but did not specify the direction of these effects and crucially, established no baseline using a control group. Because the control group lacked both prior task exposure and prior outcome valence, the current design supports what we term a two-component decomposition of prior-experience effects on subsequent decision-making: First, the contrast between the control group and both experienced groups in Block 1 establishes that the mere presence of prior task experience, independent of valence, alters early exploratory behavior. Second, the divergence between the gain and loss groups in Block 2 and in the $PVL-\Delta$ parameters isolates the additional influence of valence within the experienced groups. We do not claim that our design fully disentangles experience from valence, rather, the control group provides the baseline necessary to show that prior-experience, as a whole, shifts early decision-making, while inter-group differences implicate valence-specific effects.

Full-block modeling revealed that valence effects on choice consistency (c) were present behaviorally, but masked parameter-level differences only emerged when blocks were analyzed by phase. Consistent with the behavioral ANOVA results, early phase blocks (Blocks 1 & 2) and late phase blocks (Blocks 3–5) were fit into the model separately. Outcome sensitivity (α), was lower in the prior-experience groups compared to control group, a behavior also observed during the M-IGT suggesting that the manipulation temporarily dampened sensitivity to deck outcomes in the early phase blocks of IGT. condition-level (gain vs. loss) difference in α was stable across M-IGT and early IGT blocks, with no significant shift at the stage transition, indicating that gain and loss framing established distinct evaluative orientations during M-IGT that carried forward structurally into IGT.

In the $PVL-\Delta$ framework, a lower outcome sensitivity (α) indicates a 'flatter' utility curve, meaning that participants in the prior-experience groups were less responsive to the specific magnitudes of gains and losses in the IGT. This pattern is consistent with a temporary shift toward model-free (MF) control (Daw et al., 2005); when the utility curve is flatter, small differences in outcome magnitude are effectively compressed, making reliance on cached action values formed during M-IGT more preferable rather than updating dynamically from the new feedback of the IGT. Crucially, this cannot be attributed to inattention because if participants were globally inattentive, we would also expect reduced choice consistency (c), which was not observed. The specificity of the effect to α thus supports an MF-like valuation mechanism rather than a general attentional deficit. The initial manipulation created a dominant reference frame (the M-IGT) that temporarily constrained evaluative flexibility, persisting into early IGT blocks.

While both gain and loss experiences constrained deck choices in the early phase blocks, only loss framing (prior loss) translated into conservative choice behavior. Notably, the loss group uniquely combined reduced outcome sensitivity (α) with increased behavioral risk aversion (more C+D) in Block 2. The gain group exhibited similar reduction in (α), but did not show increased risk aversion. Thus, the reference frame established by prior gain (Kahneman & Tversky, 1979) reduced outcome sensitivity (α) comparably to losses, but this compressed valuation did not translate into conservative choice, suggesting that it is the affective charge of loss, rather than reduced sensitivity, drove risk-averse behavior in Block 2. No group differences were observed in loss aversion (λ), or choice consistency (c) during the early phase blocks, indicating that early behavioral differences were driven primarily by differences in outcome sensitivity, rather than rigid decisions.

In the late phase blocks (3-5) of the task, learning and decisions largely converged across groups, indicating that progressive accumulation of feedback due to learning of deck outcomes overrode the early framing effects. Outcome sensitivity (α) was higher in the prior-experience groups than control group, indicating that they gradually became more attuned to the magnitude of payoffs in the late phase blocks. No group differences were observed in loss aversion (λ) or choice consistency c during this phase.

Crucially, the gain group showed a significantly lower learning rate A in these later blocks compared to the control group. In the $PVL - \Delta$ context, a low A combined with high α suggests a state of controlled stability. These participants were likely aware of the feedback magnitudes, but because their A was low as they were less likely to update their established internal model based on trial-by-trial fluctuations. Essentially, the prior gain experience led to an earlier materialization of strategy. The loss group, by contrast, did not significantly differ from control on learning rate (A) at this phase, suggesting that its early risk-averse pattern changed as new feedback accumulated rather than persisting as a structural constraint on updating.

Taken together, the computational results are well aligned with the Loss Attention Framework (Yechiam & Hochman, 2013), prior loss heightened attentional engagement with outcomes which is observed as increased choice consistency (c) across all blocks, while simultaneously producing early risk-averse behavior without a corresponding change in learning rate (A). This pattern is consistent with the Framework's proposal that losses heighten attention and produce more structured, cautious decisions, rather than altering the rate of value updating. This phenomenon became visible only after the phase-level analysis.

Overall, these findings suggest that loss framing primarily operates through attentional modulation of learning and control, rather than enduring changes in valuation or loss aversion. Loss-induced attention biases early learning and risk perception, but these effects are gradually overridden as feedback accumulates and task structure becomes clear. Although our timescales were short, we were able to capture a temporary shift in decision-making strategies. Early phase blocks showed reduced outcome sensitivity (α) suggests a model-free shift where choices relied on cached values from M-IGT (Daw et al., 2005) rather than immediate feedback from deck choices. By the late phase, the gain group exhibited a theoretically important dissociation: despite recovering and elevating outcome sensitivity (high α), their learning rate (A) remained lower than control, indicating that they perceived outcome magnitudes clearly but were less likely to revise their decision policy in response to individual trial outcomes. This α–A dissociation characterises a system that is sensitive but stable which is consistent with an earlier crystallisation of strategy under prior gain experience. The loss group, by contrast, converged toward control levels on learning rate, suggesting that the early risk-averse pattern driven by attentional engagement was a transient effect.

Limitations and future scope

Our task used monetary tokens as outcomes of prior-experiences. However, in real-world decision-making, prior-experiences often involve social, emotional, or physical feedback (Loewenstein et al., 2001; Markus & Kitayama, 1991). The extent to which non-monetary frames influence decision-making remains an open question. Future studies could incorporate more ecologically valid forms of feedback to examine whether the effects of prior-experiences generalize across reward domains.

Participants in the control group completed 40 fewer trials than the prior-experience groups, confounding the absence of prior outcome valence with reduced task exposure. Future studies should incorporate a neutral M-IGT condition such that participants complete the same number of trials but receive no systematically valenced outcomes, in order to isolate valence effects from practice effects proper.

Additionally, our sample consisted primarily of young adults and was predominantly male (78%), which may limit generalizability across age groups and gender. Age is particularly relevant given evidence that older adults show increased reliance on model-free (MF), habitual control relative to younger adults (Mata et al., 2011). If baseline MF reliance shifts with age, the reference frame effects of prior experience may manifest differently in older populations.

Taken together, these limitations point toward productive directions for future work, and do not detract from the interpretability of the present findings within their defined scope.

Conclusion

The present study demonstrated that prior-experience, irrespective of loss or gain, can bias subsequent decision-making in the Iowa Gambling Task, but these effects were immediate and transient. However, the influence of prior gain or loss was largely confined to the early blocks of the task, when participants were still learning the reward structure and forming optimal strategies.

The PVL-Δ framework clarified the mechanisms underlying these early effects. Both experience groups showed reduced outcome sensitivity (α) during the initial phase, consistent with reliance on cached values from the M-IGT rather than dynamic updating from new feedback. Prior loss further combined this compressed valuation with risk-averse behavior and, across the full task, with increased choice consistency (c) – reflecting more deterministic decisions. No persistent differences in loss aversion were observed at any stage.

Together, these findings suggest that prior-experience acts as a temporary framing mechanism that biases early learning, attention, and exploration, rather than producing stable alterations in decision-making mechanisms. While a prior-experience constrains early learning in general, a prior loss exerts a specific effect on decision control (consistency), and prior gain influences strategy crystallization. As participants accumulate feedback and the task structure becomes clear, these framing-induced biases are progressively overridden, leading to convergence in learning and behavior across groups.

Conflict of interest

The authors declare no conflict of interest.

References

Ahn, W.-Y., Busemeyer, J. R., Wagenmakers, E.-J., & Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cognitive Science*, *32*(8), 1376–1402. https://doi.org/10.1080/03640210802352992

Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*, *50*(1–3), 7–15. https://doi.org/10.1016/0010-0277(94)90018-3

Bechara, A., Damasio, H., Tranel, D., & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science*, *275*(5304), 1293–1295. https://doi.org/10.1126/science.275.5304.1293

Daw, N. D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. *Nature Neuroscience*, *8*(12), 1704–1711. https://doi.org/10.1038/nn1560

Dunn, B. D., Dalgleish, T., & Lawrence, A. D. (2006). The somatic marker hypothesis: A critical evaluation. *Neuroscience & Biobehavioral Reviews*, *30*(2), 239–271. https://doi.org/10.1016/j.neubiorev.2005.07.001

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Franken, I. H. A., Georgieva, I., Muris, P., & Dijksterhuis, A. (2006). The rich get richer and the poor get poorer: On risk aversion in behavioral decision-making. *Judgment and Decision Making*, *1*(2), 153–158. https://doi.org/10.1017/S1930297500002369

Geraci, L., Miller, T. M., & De Forrest, R. (2013). The effect of retrieval cues on older and younger adults' belief in memories for actions. *Psychology and Aging*, *28*(3), 778–784. https://doi.org/10.1037/a0033326

JASP Team. (2024). JASP (version 0.18). https://jasp-stats.org

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The phq-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Lemaire, P., & Brun, F. (2018). Effects of prior-task success on young and older adults' cognitive performance an evaluation of the strategy hypothesis. *Journal of Cognition*, *1*(1), 14. https://doi.org/10.5334/joc.17

Loewenstein, G., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Maia, T. V., & McClelland, J. L. (2004). A reexamination of the evidence for the somatic marker hypothesis: What participants really know in the iowa gambling task. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(45), 16075–16080. https://doi.org/10.1073/pnas.0406666101

Markus, H. R., & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. *Psychological Review*, *98*(2), 224–253. https://doi.org/10.1037/0033-295X.98.2.224

Mata, R., Josef, A. K., Samanez-Larkin, G. R., & Hertwig, R. (2011). Age differences in risky choice: A meta-analysis. *Annals of the New York Academy of Sciences*, *1235*(1), 18–29. https://doi.org/10.1111/j.1749-6632.2011.06200.x

Rosi, A., Cavallini, E., Gamboz, N., & Russo, R. (2016). On the generality of the effect of experiencing prior gains and losses on the iowa gambling task: A study on young and old adults. *Judgment and Decision Making*, *11*(2), 185–196. https://doi.org/10.1017/S1930297500007294

Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, *56*(5), 356–374. https://doi.org/10.1016/j.jmp.2012.08.001

Spielberger, C. D. (1982). *Manual for the state-trait anxiety inventory (stai: Form y)*. Consulting Psychologists Press.

Yechiam, E., & Hochman, G. (2013). Loss-attention in cognitive tasks: Why losses persistently attract attention. *Cognition*, *131*(1), 51–61. https://doi.org/10.1016/j.cognition.2013.01.001