# Exploring the inference of outcome dependency and recency effects in repeated decision-making

Internship report

Master Cognitive Neuroscience (MCNB)

Jiani Ge

**Abstract**

Throughout the long history of research, studies in repeated decision-making have reported various patterns in which people's choices are impacted by recently experienced outcomes (recency effects). However, as the findings were derived from different experimental paradigms, task conditions, and theoretical constructs, there has been a limited understanding of the cognitive or behavioral mechanisms that underlie recency effects in general. The present project aims to explore and validate a novel conceptual framework linking recency choice behavior to decision-makers' beliefs about the dependency between choice outcomes, using a recently compiled, extensive collection of experimental data across multiple common experimental paradigms. In this report, I present the methods and results of the preliminary analyses of the effects of experimental context and the observed sequential dependency in choice outcomes, and discuss potential directions for future analyses.

# 1. Introduction

Repeated decision-making is a type of behavior that we regularly exercise in daily life and the subject of a long history of research. In contrast to one-off decisions, a central aspect of repeated decision-making is the sequential nature of the choices and outcomes, and, in particular, how experiencing and learning from the obtained outcomes may systematically impact subsequent choice behavior. A common understanding of the overall effects of learning from experienced outcomes corresponds to *reinforcement learning* – broadly, favorable outcomes increase the subsequent choice rate for the associated option, and vice versa (Estes, 1969). However, while such patterns capture the long-term, or overall effects of choice outcomes relatively well, the short-term, or local effects of choice outcomes (*recency effect*) are more contested. Rather than largely exhibiting a positive correlation between outcome favorableness and subsequent choice rate, as reinforcement learning would predict, extant studies have reported various ways in which the impact of an outcome on the next one or few choices may deviate from it. These deviating patterns are sometimes referred to together as *negative recency*, while their counterpart *positive recency* (Wills et al., 2024; Plonsky & Erev, 2017).

Often-cited negative recency effects include variants of *the gambler's fallacy*, where after a streak of the same outcomes, people expect the likelihood of the alternative outcome to be subsequently higher (Jayvik 1951; Mossbridge et al., 2017). Another group of studies suggests that people's prediction of outcomes and choice behaviors are sensitive to local sequential patterns rather than the overall trend of past outcomes (Cohen & Teodorescu, 2022; Plonsky et al., 2015; Plonsky & Erev., 2017). Additionally, Plonsky & Erev (2017) reported a 'wavy recency effect', where the effect of a rare outcome in binary lotteries is initially negative (e.g., avoiding an option after a favorable outcome) and then gradually becomes more positive.

However, despite the substantial body of literature, there has not been a unifying explanation for recency effects in the context of repeated decision-making, an inquiry that is made challenging by the multitude of variables potentially at play. Most studies focus on one type of negative recency, use different experimental paradigms (binary lottery, probability learning, etc.), and control for different task variables (outcome magnitude, valence, full or partial feedback) (Wills et al., 2024; Plonsky & Erev, 2017; Cohen & Teodorescu, 2022; Schulze et al., 2020), leaving it open as to whether the reported effects are comparable in different experimental contexts or how the task variables relate to one another.

Moreover, while discussions of (negative) recency effect often appeal to the perception and inference of local sequential patterns, there is a limited understanding of exactly how or how much these local patterns influence people's choice behaviors (see Plonsky & Erev, 2017; Schulze et al., 2020; Spiliopoulos, 2013).

The present project is part of a larger effort to systematically account for recency effects in repeated decision-making, appealing to a novel conceptual framework and an extensive collection of experimental data (Yang et al., 2024; Yang et al., 2025). The proposed conceptual framework (Figure 1) adopts a tree-like structure, where a hierarchy of factors from a priori knowledge or *belief* about the dependency between outcomes (global pattern) to the direction of the observed outcome dependencies (local pattern) determines the prevalence of positive or negative recency. We propose that while positive recency is the default choice behavior (see Scheibehenne et al., 2011, Schulze et al., 2020; Plonsky et al., 2015), people may exhibit positive or negative recency based on whether the observed or inferred dependencies between outcomes are positive or negative, when such information is available.

To test and explore the hypotheses put forward by the framework, we make use of the recently compiled Decision-from-Experience Database (hereafter *DfE database*, Yang et al., 2025). The database contains trial-by-trial data from 170 studies in 116 publications, including several common paradigms (such as lottery bandits, probability learning, and sampling), and was put together with the objective to facilitate generalizable research in experience-based learning and decision-making. The extensiveness of the database allows us to examine recency effects both across and within paradigms, and with respect to various task features such as feedback condition, decision context, outcome riskiness, valence, and magnitude.

The present report concerns the analyses conducted during an internship, which is understandably limited in scope and should only be taken as a preliminary exploration of the above-outlined framework. Specifically, the sections below report the methods and results of the following analyses: First, to investigate the hypothesis that recency effects may be, on the most global level, modulated by participants' a priori beliefs about the dependency between choice outcomes, we assessed the information available to participants before beginning the task for systematic variations. Second, for the hypothesis that, on a more local level, recency effects are modulated by observed or inferred outcome dependency, we computed the dependencies in previous trials based on outcome proportion, alternation rate, and transition probabilities. We then examined the correlation between these dependency measures and trial-by-trial recency effects. Finally, in a more exploratory manner, we also examined the correlation between recency effects and various task features, including overall outcome proportion, valence, and trial position within the repeated-decision sequence.

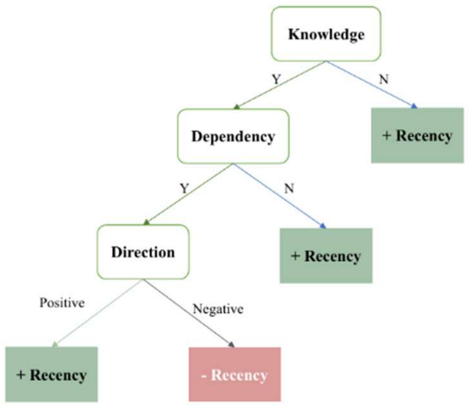



**Figure 1.** *Outline of the proposed conceptual framework.*

The tree-structure depicts how factors at different levels (global to local) may determine people's belief about the dependency in outcomes and their recency choice pattern. For example, at the most global level, if knowledge or inference about outcome dependency is unavailable, people would act in accordance with positive dependency by default. Otherwise, the choice behavior is further influenced by more local factors such as the observed dependency in the past trials. (Figure taken from Yang et al. (2024)'s poster presentation at the 46th Annual Conference of the Cognitive Science Society)

## 2. Methods

### A priori belief about outcome dependency

To investigate the effects of participant's a priori beliefs about the dependency between choice outcomes on recency choice behavior, we examined the experimental procedure and task instructions of studies under the lottery bandit (41) and probability learning (26) paradigms in the DfE database, and recorded information that may lend to such beliefs (e.g. experiment format – compared to a computer program, an experimenter that manually hands out feedbacks may be perceived as more agentic and less random).

### Observed outcome dependency and recency effects

To investigate the hypothesis that recency effects are modulated by observed or inferred outcome dependency from previous trials, we used Hidden Markov Models (HMMs) to predict the decision outcome on a trial-by-trial basis, based on the three basic types of sequential dependency – outcome proportion, alternation rate, and transition probabilities. The choice is motivated by the fact that basic dependency measures, as well as inferences via HMMs, have been shown to be cognitively realistic for various datasets in the cognitive processing of sequential dependency (Meyniel et al., 2016). We then examined the correlation between the inferred outcomes based on sequential dependency and recency choice behavior. Due to time constraints, we have only applied the analysis to lottery bandit data.

### Exploratory analysis

We additionally examined the potential correlations between recency effects and various task features. On task-level, we examined the effects of feedback condition, rare outcome valence, magnitude, and overall proportion. On trial-level, we examined the effects of trial position within the decision sequence.

## 3. Results

### A priori belief about outcome dependency

Of the 67 studies we examined (41 lottery bandits, 26 probability learning), we did not find systematic differences in experimental procedure or task instruction that might lead to different beliefs about outcome dependency. Most studies implemented the task in an abstract, virtual format with minimal information regarding the mechanism that generates outcomes (see Table 1 for details).

| Paradigm | Without context | With context |
|---|---|---|
| Lottery Bandits | 32 | 9 (3 financial tasks + 3 graphic display + 3 in-person experiment) |
| Probability Learning | 20 | 6 (2 game-narrative + 4 physical outcome (food reward)) |

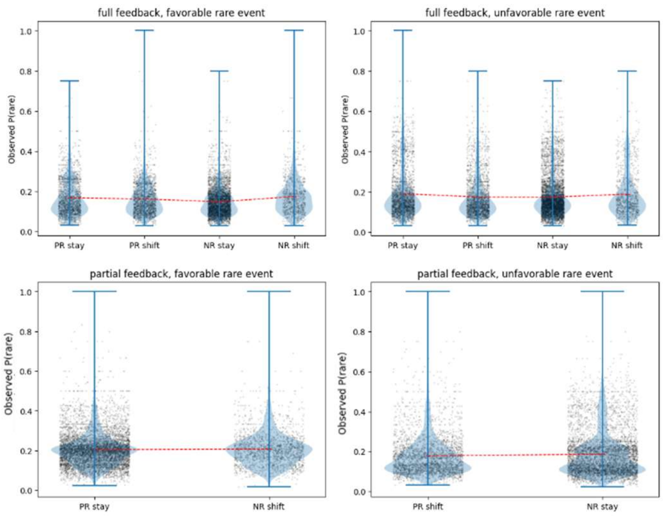
**Table 1.** *Variation in experimental context in lottery bandits and probability learning studies in the DfE database.*

### Observed outcome dependency and recency effects

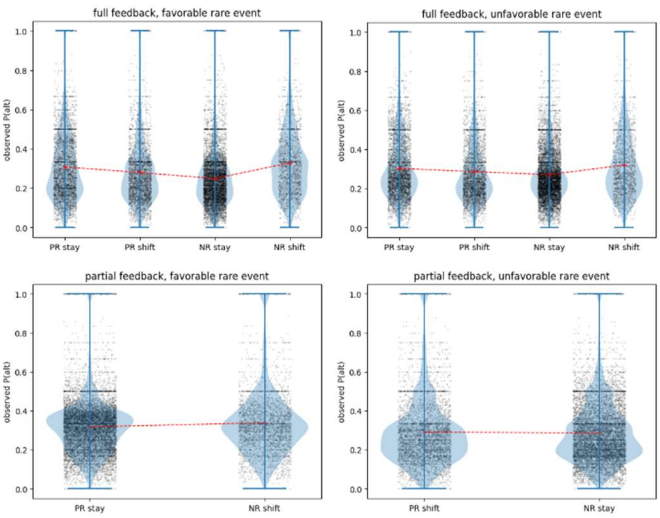
To examine the effects of sequential dependency in observed outcomes on recency choice behavior, we divided the data into four groups based on the type of risky outcome (whether the rare outcome is *favorable* or *unfavorable*) and the feedback condition (whether the forgone outcomes are observable (*full*) or not (*partial*)), as previous findings suggest that these task features may interact with recency effects (Plonsky & Erev, 2017, Wills et al., 2024; Yang et al., 2024). Then, for each group, we divided recency choice behavior into four categories, based on whether the recency effect is positive or negative, and whether the choice behavior itself is a repeat ("stay") or switch ("shift") from the last choice, to account for the potential effects of *inertia*, or the tendency to repeat the last choice in lottery bandit tasks (Yang et al., 2025). For all the subgroups of the lottery bandit data and all three sequential dependency measures, we did not find evidence that the four types of recency choice behavior correspond to the sequential dependency of previously observed outcomes on either trial or task-level (see Figure 2 and 3).

In addition to computing sequential dependency based on all past outcomes, we also implemented the inference based on a limited number of past outcomes, which may be more cognitively realistic. As preliminary analyses, we chose the parameters for the memory window (4, 6, 8, 12, 16) and the exponential decay factor (6, 8, 12, 16, 20) arbitrarily, covering the range of values that Meyniel et al. (2016) used to successfully reconstruct neurophysiological data of sequential perception. These manipulations also did not yield any correlation between the sequential dependency of past outcomes and recency choice behavior.

**a. Dependency based on outcome proportion**




**b. Dependency based on alternation rate**




**c. Dependency based on transition probability**

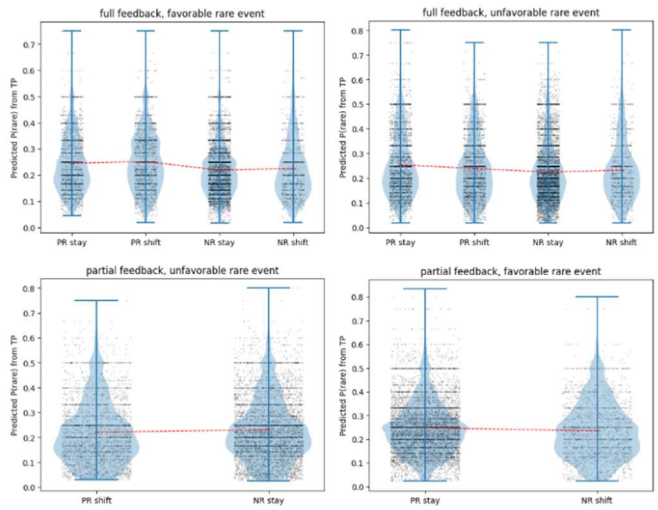



**Figure 2.** *Observed dependency and recency effects after rare events (trial-level).*

In each panel, values along the y-axis are either sequential dependency measures (*a* and *b*) or inferred likelihood of rare outcome for the next trial (*c*). In all three cases, the values do not substantially differ for the four types of recency choice behavior. (PR = positive recency; NR = negative recency)

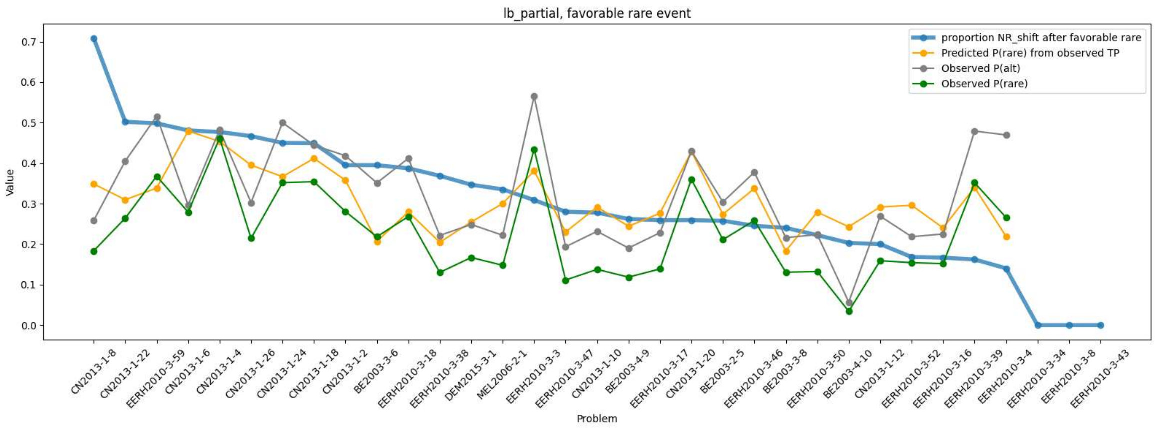


**Figure 3.** *Observed dependency and recency effects after rare events (task-level).*

Along x-axis, each experimental task is ordered by the aggregated proportion of negative recency (in blue). The aggregated sequential dependency values are plotted for each task in orange, grey, and green. There is no visible correlation between these measures and negative recency rate. Here, for brevity, we only present the figure for partial feedback lottery with favorable rare events. The results for other tasks were similarly uncorrelated.

**Exploratory analyses**

As shown in Figure 4, there is some difference in negative recency rate when grouped by feedback condition (full or partial), rare outcome valence, and the type of choice behavior (stay or shift). Then, for each combination of these variables, we plotted the correlation between rare outcome probability, magnitude, and relative magnitude (to the non-rare outcome), and did not find strong correlations for any individual variables (Figure 5). We also divided choice-sequences into blocks (10-trial and 20-trial, see Figure 6 for example) and computed the proportion of recency effects for each block. We did not find systematic changes in the proportion of recency effect through the course of the experiment.

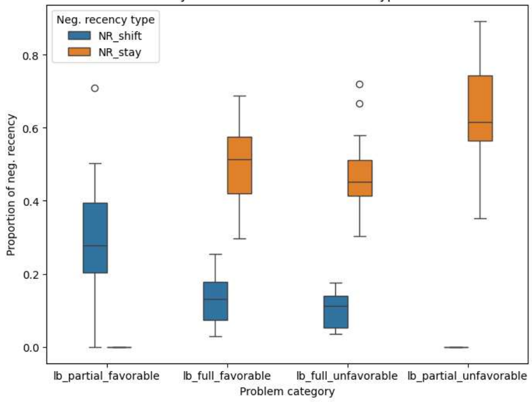
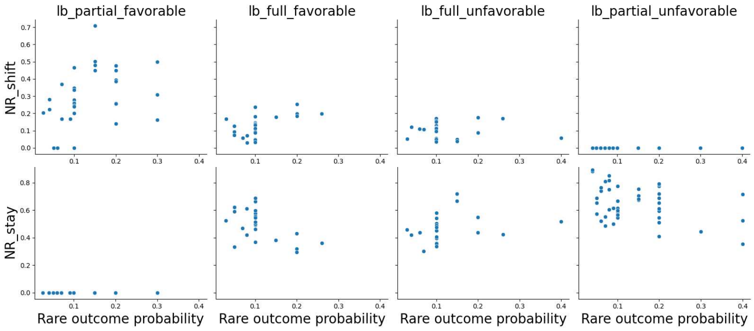
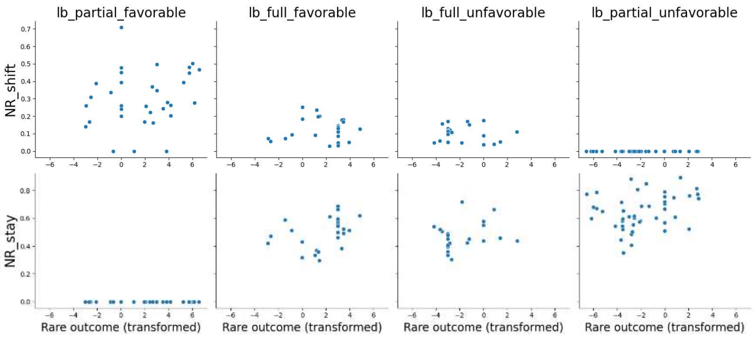


**Figure 4.** *Overall proportion of negative recency in lottery bandits studies, grouped by feedback condition and rare outcome valence.*

**a. Negative recency rate and rare outcome probability**




**b. Negative recency rate and rare outcome value (transformed)**




**c. Negative recency rate and rare outcome value (relative to non-rare outcome)**

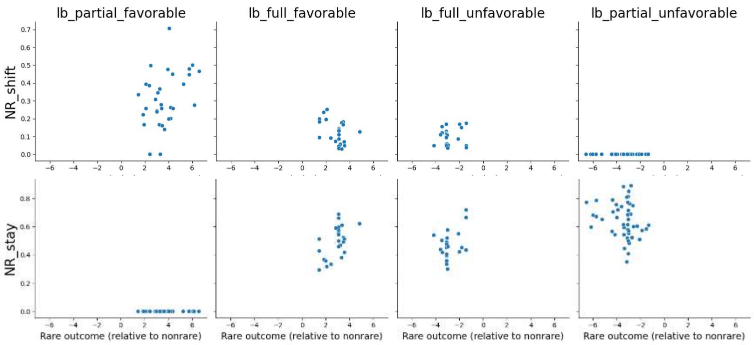



**Figure 5.** *Scatterplot of proportion of negative recency and aggregate task features.* Top, middle, and bottom panel plots negative recency rate against rare outcome probability, rare outcome value (arcsinh transformed to accommodate extremely large/small values), and rare outcome value (relative to nonrare outcome), respectively. There seems to be more variation between the task groups (feedback, outcome valence) than within.

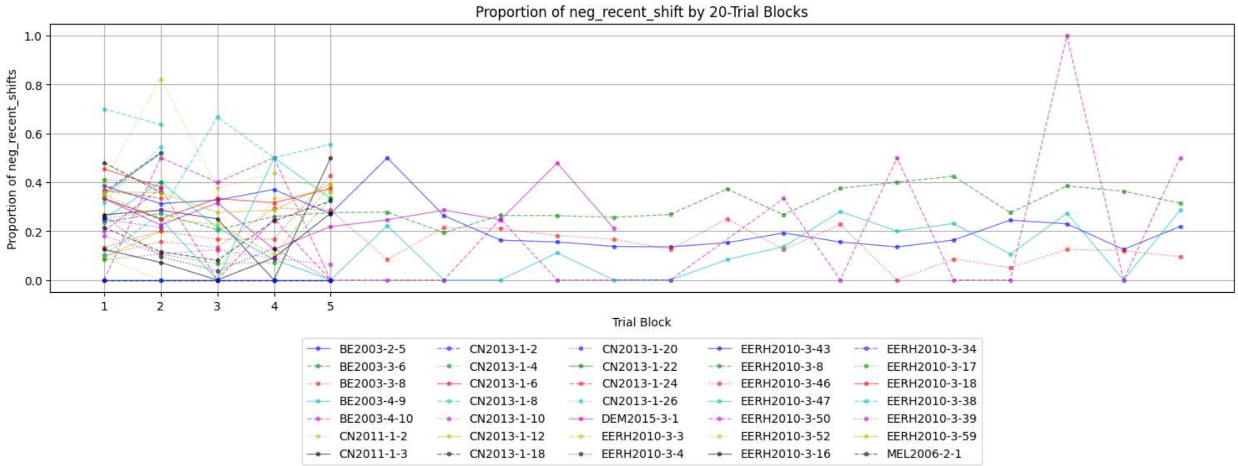



**Figure 6.** *Proportion of negative recency (shift) in 20-trial blocks.*

Each line can be seen as the shift in negative recency rate over the course of choice sequences, aggregated by task. There does not seem to be a consistent pattern across tasks. Here we only present partial feedback with positive rare outcome tasks as an example. Other groups of tasks, similarly, do not show systematic patterns.

## 4. Discussion

### Discussion of analysis results

Contrary to the expectation that participants may form a priori beliefs about outcome dependency that influence their recency choice behaviors, we found that experimental instructions are typically abstract and minimal. The few studies that provided more qualitative information, such as using human experimenters, framing decisions in a narrative context, or explicitly stating that trials are independent from each other, do not consist a large enough sample for testing of systematic differences. We are hence unable to test the hypothesis regarding the effects of experimental context this way. However, within the scope of the database, the hypothesis may still be addressed by examining the effects of experimental paradigms, which may facilitate different expectations about the outcome-generating mechanisms. This would be a potential subject for future inquiries.

In our second analysis, we used sequential dependency measures of observed outcomes (proportion, alternation rate, transition probability) to infer the outcome of the next choice, and did not find a correlation between the inference and participants' recency choice behavior. Contrary to the prediction that, for example, negative recency choices may be preceded by outcome sequences that were more negatively correlated, the observed outcome sequential dependencies for the four types of recency effects were largely the same.

Admittedly, our sequential dependency measures are rather simplistic and may not be sensitive enough to capture the intended effects. We have chosen the analyses considering that the processing of basic sequential dependencies is a robust cognitive phenomenon corroborated in various research domains (Meyniel et al., 2016), and with the assumption that the extensiveness of our database would allow behavioral patterns to be detected, even given the heterogeneity of task features between studies. The null results suggest that these assumptions may have been overly simplifying. One approach for future analyses would be to take into account more task variables that potentially interact with recency effects, such as outcome magnitude. Additionally, we may also employ more nuanced operationalization of sequential dependency, such as also using count- and distance-based metrics, or even language-like structures (Planton et al., 2021) or a hierarchically-organized set of features (Maheu et al., 2022). Similarly, we may also expand the definition of recency effect so that it applies to all trials rather than only the ones after rare outcomes.

In the exploratory analyses, we looked at the effects of feedback condition, outcome valence, proportion, and magnitude on the prevalence of recency effects. None of these variables exert a strong influence individually. We have also examined their potential interactions preliminarily (via visualization). While dividing the tasks by feedback condition and outcome valence account for some variation in negative recency proportions (Figure 5), the effects of outcome magnitude and proportion on top of the division seem to be minimal (Figure 6). However, this is an admittedly simplistic approach. In future projects, it would be more appropriate to use observed/experienced (rather than preset) outcome features and more systematic multivariate analysis methods.

**General Discussion**

In summary, the present project is part of the larger objective to develop a unifying framework for sequential processing and recency effects in repeated decision-making. The analyses conducted thus far suggest that using simple dependency measures such as alternation rate and transition probability, and categorizing recency effects only based on the direction of one subsequent trial and whether the choice is a shift or repeat may not be sufficient to account for the effect, given the many potential confounding variables. The results do not present conclusive evidence for or against the proposed framework outlined in Section 1. As suggested above, the objective of the next steps would be to refine the operationalization and computation of sequential dependency measures and recency effects to allow for a more sensitive, as well as cognitively realistic, modeling and analysis.

In particular, we have defined recency effect with respect to rare events, as the it is often discussed as such and in relation to the well-researched phenomenon of over- and under-weighting rare events in repeated decision-making (Plonsky & Erev, 2017; Wulff et al., 2018; Barron & Yechiam, 2009; Nevo & Erev, 2012). However, it is likely that this definition is unduly restrictive, both limiting the data available for analyses and drawing arbitrary distinctions with respect to other recency choice behavior that occurs without a rare outcome (e.g., classic gambler's fallacy, see also Wills et al. (2024)).

A particular limitation of the present analyses of sequential dependency could be due to the focus on lottery bandit studies, where trial outcomes are typically numeric (e.g. +10 vs. -1) rather than 0/1 (or True/False). The magnitude, or value, of outcomes is asymmetric within a task and highly inconsistent between tasks. While in Meyniel et al. (2016) the HMMs worked well for binary sequences, it might be more appropriate to additionally incorporate variables that account for sequence item values for our data. Though this kind of additions, along with more nuanced operationalization of recency effects and sequential dependency, would increase model complexity, it may be justified if done in an incremental and controlled manner. It would contribute to a more cognitively realistic representation of decision outcomes, and does not subtract from generalizability, as the approach would still operate under the assumption that there is a common cognitive mechanism relying on the processing of sequential dependency information that underlies recency effects, or the short-term, local effects of learning from experience.

# References


Ayton, P., & Fischer, I. (2004). The hot hand fallacy and the gambler's fallacy: Two faces of subjective randomness? *Memory & Cognition*, *32*(8), 1369–1378. https://doi.org/10.3758/bf03206327

Barron, G., & Yechiam, E. (2009). The coexistence of overestimation and underweighting of rare events and the contingent recency effect. *Judgment and Decision Making*, *4*(6), 447–460. https://doi.org/10.1017/s1930297500003983

Cohen, D., & Teodorescu, K. (2022). On the effect of perceived patterns in decisions from sampling. *Decision*, *9*(1), 21–42. https://doi.org/10.1037/dec0000159

Estes, W. K. (1969). Reinforcement in human learning. *Reinforcement and Behavior*, 63–94. https://doi.org/10.1016/b978-0-12-683650-9.50008-x

Maheu, M., Meyniel, F., & Dehaene, S. (2022). Rational arbitration between statistics and rules in Human sequence processing. *Nature Human Behaviour*, *6*(8), 1087–1103. https://doi.org/10.1038/s41562-021-01259-6

Meyniel, F., Maheu, M., & Dehaene, S. (2016). Human inferences about sequences: A minimal transition probability model. *PLOS Computational Biology*, *12*(12). https://doi.org/10.1371/journal.pcbi.1005260

Mossbridge, J. A., Roney, C. J., & Suzuki, S. (2017). Losses and external outcomes interact to produce the gambler's fallacy. *PLOS ONE*, *12*(1). https://doi.org/10.1371/journal.pone.0170057

Nevo, I., & Erev, I. (2012). On surprise, change, and the effect of recent outcomes. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00024

Planton, S., van Kerkoerle, T., Abbih, L., Maheu, M., Meyniel, F., Sigman, M., Wang, L., Figueira, S., Romano, S., & Dehaene, S. (2021). A theory of memory for binary sequences: Evidence for a mental compression algorithm in humans. *PLOS Computational Biology*, *17*(1). https://doi.org/10.1371/journal.pcbi.1008598

Plonsky, O., & Erev, I. (2017). Learning in settings with partial feedback and the wavy recency effect of rare events. *Cognitive Psychology*, *93*, 18–43. https://doi.org/10.1016/j.cogpsych.2017.01.002

Plonsky, O., Teodorescu, K., & Erev, I. (2015). Reliance on small samples, the wavy recency effect, and Similarity-based learning. *Psychological Review*, *122*(4), 621–647.

https://doi.org/10.1037/a0039413

Scheibehenne, B., Wilke, A., & Todd, P. M. (2011). Expectations of clumpy resources influence predictions of sequential events. *Evolution and Human Behavior*, *32*(5), 326–333. https://doi.org/10.1016/j.evolhumbehav.2010.11.003

Schulze, C., Gaissmaier, W., & Newell, B. R. (2020). Maximizing as satisficing: On pattern matching and probability maximizing in groups and individuals. *Cognition*, *205*, 104382. https://doi.org/10.1016/j.cognition.2020.104382

Spiliopoulos, L. (2013). Beyond fictitious play beliefs: Incorporating pattern recognition and similarity matching. *Games and Economic Behavior*, *81*, 69–85. https://doi.org/10.1016/j.geb.2013.04.005

Wills, A., Schlegelmilch, R., & von Helversen, B. (2024). Reward Count(s): Negative Recency in Probabilistic Experience-Based Learning. 3421. Paper presented at 46th Annual Meeting of the Cognitive Science Society, Rotterdam, Netherlands. https://escholarship.org/content/qt4c20293n/qt4c20293n.pdf

Wulff, D. U., Mergenthaler-Canseco, M., & Hertwig, R. (2018). A meta-analytic review of two modes of learning and the description-experience gap. *Psychological Bulletin*, *144*(2), 140–176. https://doi.org/10.1037/bul0000115

Yang, Y., Mikhail, S., Thomas, A., Hertwig, R., & Wulff, D. (2025). *The Decisions-from-Experience Database.* Max Planck Institute for Human Development. [Manuscript]

Yang, Y., Thoma, A., Hertwig, R., & Wulff, D. (2024). *On the nature of recency after rare event in decisions from experience*. [Conference abstract and poster]. https://escholarship.org/uc/item/0np8n2fm