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Retrospective Evaluations of Gambling Wins:
Evidence for a 'Peak-End' Rule

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Abstract

This study explored retrospective evaluations of temporally extended outcomes. Participants, primarily non-gamblers or recreational gamblers, played a fruit machine that presented sequences of payouts and then retrospectively evaluated their experiences. Experiments 1 and 2 replicated a robust "peak-end" effect on estimation judgments and choices, with participants exhibiting biases in favor of sessions with high peak-end values. Experiment 3 used modified stimuli that reduced the payout structure to wins and non-wins (no extreme values) and found no effect; we suggest this may arise from the influence of sensitivity to affect. Analysis across conditions found a consistent underestimation of total winnings and frequency of wins, in support of memory-based evaluation strategies. Consequences of these findings for gambling judgments and decisions are discussed.

Keywords: estimation; frequency; gambling; peak-end; retrospective evaluation.

Introduction

Watching one of the year's Oscar-tipped films might mean a rollercoaster ride through an intense drama played out through fight scenes, love scenes and, more than likely, boring dialogue and long looks at the scenery. Despite the range of emotions you might feel during the movie, you can probably still tell your friend the next day that the film was "not bad" or maybe even "pretty good".

An essential distinction here is between *instant* and *remembered* utility. While instant utility is the pleasure or pain we feel at a moment—a fleeting feeling that is replaced by the next moment's instant utility—remembered utility is the global assessment we make retrospectively that encompasses those moments and becomes our memory for the experience. While both are useful constructs in their own right, a conflict between the validity of a person's total utility (sum of instant utilities) and remembered utility of an experience emerges when evaluating *temporally extended outcomes* (TEOs), or experiences that take place over time (Kahneman, Wakker, & Sarin, 1997).

Previous research has explored the utilities of TEOs in a range of contexts, including film clips (Fredrickson & Kah-neman, 1993), medical procedures (Redelmeier & Kahne-man, 1996) and sounds (Schreiber & Kahneman, 2000). In these experiments, researchers arrived at three main findings that indicate a conflict between the remembered and instant utilities of past episodes: the peak-end rule and its two related effects of duration neglect and violations of "monotonicity". In this study, we focus on the peak-end rule.

The peak-end rule states that a simple average of the instant utilities (or disutilities) felt at the peak intensity of an experience and at the end of an experience determines the global assessment given retrospectively. For example, consider Redelmeier & Kahneman (1996), a study of patients' retrospective evaluations of colonoscopies. Patients experienced the same routine procedure, but doctors prolonged the experience for some, adding additional pain at a lower intensity. Although the patients in the shorter procedure group experienced objectively less pain, they rated their experience more negatively than the patients in the longer procedure group. Patients' future choices and memories for the pain felt during the colonoscopies matched a peak-end average better than an aggregation of total disutility.

While previous research has provided strong evidence for the peak-end rule and catalogued its factors and behavior to some depth (see Schreiber & Kahneman, 2000), there still remain questions about its determinants and applicability. The research field to this point has focused on passively experienced and primarily sensory stimuli to evoke hedonic responses, such as colonoscopies and aversive sounds. But how does the peak-end rule fare when experiences are actively generated? And does it apply for monetary, and hence only indirectly hedonic, stimuli?

Peak-End in Monetary Sequences

Sequences of monetary gains or losses are common experiences in the real world. Regular bills and payments are ubiquitous and the ability to make accurate retrospective judgments about them may have a serious impact on our decision making.

Economic theory would have our judgments of monetary sequences follow normative rules, such as maximizing the average or total money gained or lost; rational people prefer more money to less. Langer, Sarin and Weber (2005) tested this concept and observed that, rather than use normative rules, people overweighed peak-end values. However, the result was not found in tasks of little affective experience; the effect was strongest on performance-based tasks. The extension to monetary sequences is still unclear. Gambling outcomes are yet more ambiguous: gambling has acutely hedonic wins and losses but also cognitive biases such as illusion of skill, tendency to scrutinize losses, or inclination to transform losses into "near-misses" (Gilovich, 1983).

Estimating Sums and Frequencies over Time

The objective nature of monetary stimuli broadens the scope of possible analyses beyond that of previous research. In addition to peak-end choice evaluations comparing sequences, these experiments can also examine numerical inference and frequency estimation, two concepts central to fundamental cognitive processes and particularly critical to gambling judgments and decisions.

Most of the numerical estimation literature focuses on numerosity or magnitude, largely neglecting the problem of arithmetic involving sequences. Results from Langer, et al. (2005) suggest that subjects keep running totals, but this was found for sequences of 10 or fewer numbers under the explicit direction to attend to the sequences. It is still unknown how subjects evaluate longer trials, which resemble real world scenarios that persist beyond 10 instances (a session at a fruit machine might continue beyond 100 spins).

In contrast, there is a rich literature studying frequency estimation (Sedlmeier & Betsch, 2002). Comparisons across paradigms and stimuli have resulted in conflicting conclusions about our ability to accurately encode frequencies. We will study this here with a simplified comparison of wins and non-wins to see how affective experience might contribute to the debate.

Aims of This Study

We report three experiments using monetary stimuli to explore the peak-end rule and estimation of sequence sums and frequencies. Experiments 1 and 2 establish support for the peak-end effect for monetary sequences in contrast to alternative models while also demonstrating a consistent underestimation of the sequentially-presented sums. In Experiment 3 designed to reverse the peak-end effect, participants do not use the peak-end rule, as expected, and continue to underestimate sums and frequencies.

Experiment 1

We designed payout sums for two sessions such that Session-Peak paid less but had high peak-end values, while Session-Random paid more and followed a random pattern with no extreme payouts. Normative maximizing behavior (e.g., using a rule such as maximizing total session payout) predicts preference for higher-paying Session-Random, as
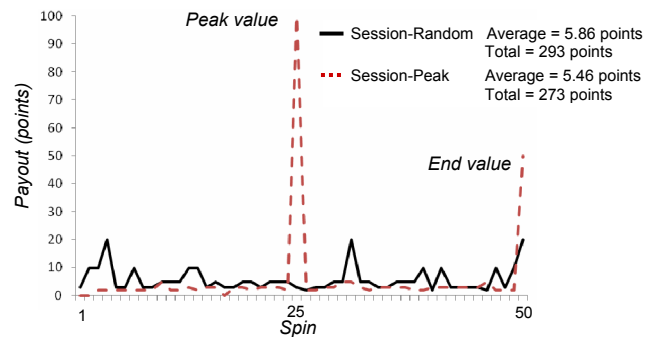

Figure 1: Example payout stimuli for Experiment 1

extreme values should have no effect on evaluations. In contrast, the peak-end rule predicts preferences and estimation judgments biased in favor of Session-Peak.

Method

Design and Materials The experiment used a within-subjects design and a fruit machine simulation played for 2 sessions, each lasting 50 spins. The simulation appeared to function like an actual fruit machine, though running on a conventional PC; there was no cost to play on each trial. Participants clicked a button to activate the spinning of the machine's reels and several seconds later, when the reels came to a stop, the value of points awarded based on the combination of symbols was shown for one second. The program then waited for the participant to spin again. The machine did not show cumulative winnings.

The two fruit machine sessions were similar; however, the session averages and total payouts were varied, as described in Figure 1. Session-Peak was lower in average spin outcome and lower in overall winnings but had high peak and end values. These extreme payout values were excluded from any other spin outcome to ensure the peak characteristic. Session-Random followed a random pattern of payouts with no extreme values. The order in which the participants saw each session was counterbalanced.

Three evaluations questions were included. A question aimed at hedonic evaluation asked participants to choose which of the two sessions they most enjoyed. An informational question asked participants to estimate how many points they had won in each session. A choice evaluation prompted participants to choose at which machine they would prefer to play an additional high-stakes session.

Participants Twenty-four participants (10 female) were recruited via the UCL Psychology Subject Pool and paid for participation. Ages ranged from 19 to 67 years (M = 29).

Procedure Participants were told they would play a virtual fruit machine on the computer and afterwards answer questions about their experience, and that they would be compensated for their time. The computer program presented instructions for operating the fruit machine and provided a payout table listing the combinations of symbols and their payouts. During the fruit machine session, the participants

controlled the speed at which the session progressed, but the duration of presentation of payout remained constant at 1.5 seconds. The end of the first session was followed by a short break of a blank screen before the start of the second session. After completing the second session, the program prompted the participant to answer the evaluation questions, one at a time, in a random order except with the preference question (at which machine they preferred to play again) always appearing last.

Results and Discussion

Estimations A comparison of the means for the participants' estimated values shows that participants identified Session-Peak as significantly higher-paying than Session-Random ($z = -1.67$, one-tailed $p < .05$). Participants mistakenly identified the lower-paying session as higher-paying.

Figure 2 shows a significant underestimation of total payout across both sessions. Comparisons of the actual and estimated values for each session confirm significant differences (Session-Peak: $z = -3.83$, $p < .001$; Session-Random: $z = -4.14$, $p < .001$). The data show fundamental errors in estimation of the sum of a sequence of numbers. This may be because the participants' "losses" lingered with them longer than their wins (as the machine gave only positive or zero payouts, losses in this experiment equate to not winning any points on a spin). As Gilovich (1983) found, people may spend more time after gambles thinking about their losses and remember more information about them.

Peak-End Analysis of participant estimates suggests that the presence of high peak-end values created an upward bias. A repeated-measures ANOVA found a significant effect of the peak-end manipulation for the differences between session total payouts and participant estimates ($F(1,22) = 7.18$, $p < .01$). In other words, although estimates for both sessions were far below actual values, participants' estimates for Session-Peak were significantly closer to actual values than for Session-Random.

Choice Behavior Analysis of the hedonic and choice data (proportion enjoying Session-Peak most, 46%; proportion preferring to play Session-Peak again, 54%) found that choices were not significantly different from chance (enjoyment: $t(23) = -.40$, ns; preference: $t(23) = -.40$, ns).

Summary The results extend previous research by establishing the peak-end rule's effect on estimations of monetary winnings. The data show that participants' evaluations are significantly distorted upwards by an emphasis on the peak and end values.

After establishing the peak-end and underestimation effects with monetary sequences, the second experiment aimed to replicate and confirm these results and explore the boundaries of these effects.
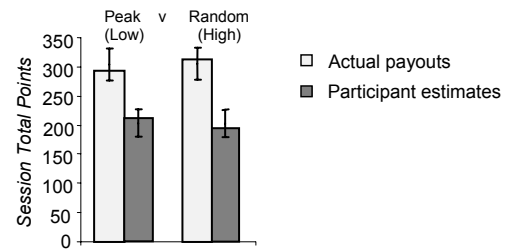

Figure 2: Participant estimates for Experiment 1

Experiment 2

To understand participants' baseline retrospective evaluations, conditions comparing two Sessions-Random (both sessions free from extreme payout values) were included. To explore the boundaries of the peak-end rule, conditions comparing session pairs with large differences and also small differences between them were also added. We expected a repeat of the behavior found in Experiment 1 for the small difference condition and a slightly stronger set of results for the large difference condition, reflecting the weakening of the peak-end effect as the two session pairs' total payouts converge.

Method

Design and Materials This experiment closely mimicked the within-subjects set up of Experiment 1. Participants played the fruit machine simulation with sessions shortened to 25 spins each, resulting in a total of 300 spins over 12 sessions. Participants were presented two sets of conditions: a set in which the differences between the two conditions were 30 points and a second set in which the differences were 15 points. Within each set, participants saw three pairs of sessions. A control pair compared two random sessions. Two pairs compared sessions on a 2 (presence of high peak-end values) x 2 (relative position) framework similar to the design of Experiment 1. This is described in Table 1 below.

Table 1: Conditions A-F for Experiment 2

	Large Difference			Small Difference	
	Higher	Lower		Higher	Lower
A	*Random*	*Random*	**B**	*Random*	*Random*
C	*Random*	*Peak-End*	**D**	*Random*	*Peak-End*
E	*Peak-End*	*Random*	**F**	*Peak-End*	*Random*

Payout design repeated that of Experiment 1; however, the range of stimuli was restricted due to the shortened length of sessions. Peak values were set to 50 points on the 12th spin and end values set to 25 points on the 25th spin.

Participants evaluated their experiences after each session pair. Evaluation questions matched those of Experiment 1.

Participants Seventeen participants (11 female) were recruited via the UCL Psychology Subject Pool and told they would receive a set payment for their time and an opportunity for bonus pay dependent on performance in the experiment. Ages ranged from 21 to 67 years ($M = 30$).

Procedure The procedure followed that of Experiment 1 for each condition. After evaluating each pair of sessions, the program looped and presented the next pair of sessions and evaluations. After eight sessions, the program presented a reminder of the bonus payment contingent on performance. The order of conditions and the order of sessions within each condition were randomized.

Results and Discussion

Baseline Conditions To establish a baseline model of retrospective estimations, repeated-measures ANOVAs were used to analyze participants' estimations for control conditions A and B. Participants were able to distinguish between the two sessions and correctly identify which session was higher-paying (Large difference: $F(1,16) = 38.47$, $p < .001$; Small difference: $F(1,16) = 4.64$, $p < .05$). Across conditions, estimates were significantly lower than actual sums ($t(67) = 6.78$, $p < .001$). The leftmost data in Figure 3 compare the actual session sums in each condition side by side with participants' estimations.

Preference data assessing participants' hedonic evaluations confirmed the informational estimation findings. For the larger difference condition (A), all participants preferred the higher-paying session, as expected. However, the smaller difference condition (B) produced weaker results: only 76% of participants preferred the higher-paying session.

This analysis provides confidence in people's ability to discriminate between higher- and lower-paying sessions. Additionally, the trends match expectations that small 15-point differences would be difficult but still manageable for participants to distinguish. These estimation performances represent unbiased estimations and benchmarks for comparison to experimental conditions.

Experimental Conditions A repeated-measures ANOVA was run to compare estimates of the experimental condition session sums. Analysis found that, as expected, the presence of high peak-end values had a significant upwards effect on estimations of sums ($F(1,16) = 5.63$, $p < .05$). In line with Experiment 1 and the peak-end rule, this finding indicates that the presence of high peak-end values distorts estimations. Participants' estimates for sessions with high peak-end values (summed across conditions, M = 127.87, se = 4.84) were higher than for those without (M = 118.24, se = 6.89). No interactions were significant.

To take a closer look at the data, Figure 3 compares the actual session sums in each condition side by side with estimations. Across all conditions, participants' estimations are significantly lower than actual sums ($t(135) = 7.10$, $p < .001$), with a mean difference of more than 19 points.

Choice data for the experimental conditions were compared to their baseline counterparts. For example, experimental conditions with a large difference between session sums were compared to the baseline condition with a large difference between session sums. Nonparametric analysis found significant effects for the large difference conditions (comparison between A and C: $z = -2.24$, $p < .05$), showing that many participants mistakenly preferred the lower-paying

session, as suggested by the previous finding of distorted estimations and in support of the peak-end rule.
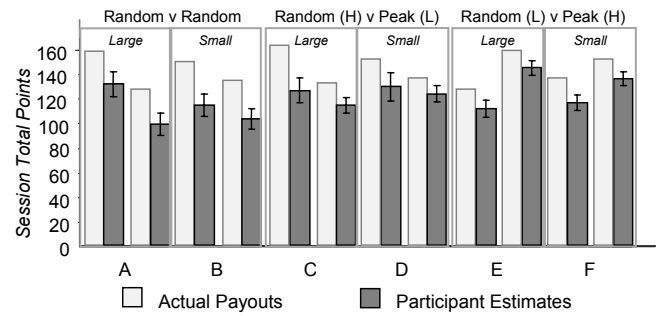

Figure 3: Participant estimates for Experiment 2

Results across Experiments 1 and 2 Collating across all session evaluations (n = 252), a robust result emerges. Participants underestimated session sums across all conditions ($z = -10.68$, $p < .001$). Using error percentage (because sums varied between sessions, a standardized measure of error was used, with actual session total as a base), mean underestimation was 19.43%. Additionally, the peak-end bias held ($t(250) = 2.22$, $p < .05$).

Summary Overall, the findings confirm the results of Experiment 1 in support of upwardly biased estimates in the presence of high peak-end values and underestimation across all conditions. Compared to baseline conditions, participants were worse at estimating session sums and made suboptimal decisions when asked to choose between sessions where one had high peak-end values. Additionally, the manipulation of the size of the difference between sessions within a condition found that 15 points approximates a threshold for the peak-end bias.

These findings were replicated even with a reduced number of payouts (Experiment 1: 50 spins per session; Experiment 2: 25 spins per session) and complete information regarding the evaluation task. Participants knew they would be asked to estimate sums before seeing the sequences of payouts but still did not overcome the underestimation and peak-end biases.

Given that participants made these estimation errors yet managed consistent relative judgments between session pairs, it seems likely that participants are using a memory-based estimation strategy rather than an online encoding strategy. Participants may be retrieving instances of payout outcomes and extrapolating using a consistent calculation. Such processes have been found to produce underestimations in frequency judgments (Brown, 1995).

To explore frequency estimations in sequences of monetary values, Experiment 3 uses a simplified payout structure of wins and non-wins. Given the task (gambling), it was expected that participants would naturally attend to win and non-win frequencies and perform well on frequency evaluations. Additionally, the experiment addresses two design concerns, incentives and comparison judgments. Although

the participants received a performance-related bonus payment in Experiment 2, this incentive may not have been strong enough to approximate realistic fruit machine gambling behavior; Experiment 3 uses a more realistic machine environment. Similarly, the comparative judgment design may also be producing unique results that do not generalize to single session evaluations.

Experiment 3

To enable the exploration of frequency estimations and maximize control over the payout stimuli and manipulations between participants, the third experiment used a simplified payout stimuli structure. However, while this modification was expected to lead to accurate frequency estimations, we expected these modifications to lead to a decreased dependency on the peak-end heuristic, or any related availability heuristic, as the peak value was no longer high and unique.

Method

Design and Materials A modified payout table used 0 and 30 pence outcomes, resulting in a straightforward payout pattern of wins and non-wins. In a 2x2 between-subjects design, the presence of both long "peak" and "end" streaks were manipulated. Peaks were represented with a long streak of nine wins. Ends were represented by nine spin outcomes, with a positive end denoted by a positive trend (five non-wins followed by four wins) or a negative end (four wins followed by five non-wins). The number of wins and, therefore, session total payout was held constant across conditions. A cost to play was charged, with each spin deducting 10 pence from an endowed bank. This was illustrated by an animation of a coin being put into the fruit machine for each spin. Stimuli were randomized as previously and each session consisted of 90 spins.

Retrospective evaluations were modified to reflect the change to single-session evaluations. The informational question was modified to consider the endowment and cost to play modifications, asking how much the participant thought was left in his or her bank. The question set also included a frequency and streak evaluation, asking how many times the participant had won and what was the length of their longest streak of consecutive wins. The South Oaks Gambling Screen (SOGS) was given at the end of the experiment to assess gambling experience.

Participants Forty-eight participants (29 female) were recruited from the UCL Psychology Subject Pool and compensated based on their performance on the task. Participants were randomly assigned to the two conditions. Analysis of SOGS scores identified 24 participants as having no problem with gambling and 22 as having some or serious problems (scores above 1, including 2 probable pathological gamblers).

Procedure Participants were told at the start of the experiment that they were being given a bank of £7.00 with which to play a fruit machine, and they would keep however much

was left upon completion. Participants then heard and read instructions on how to operate the machine, played one session and gave retrospective evaluations.

Results and Discussion

Peak-End The effect of manipulations of the peak streak of wins on participant estimations of total winnings and estimates of win frequency were non-significant (totals: $F(1,46) = .00$, ns; frequency: $F(1,46) = .90$, ns). Likewise, manipulations of end streaks were also non-significant (totals: $F(1,46) = .12$, ns; frequency: $F(1,46) = 1.99$, ns). Additionally, the data show that, although participants in the conditions with "peak" streaks recognized the streak ($F(1,46) = 35.75$, $p < .001$), it had no significant effect on their evaluations. There were no main or interaction effects on any measure for the SOGS score.

Estimation Although there were no differences between the conditions, there was significant underestimation of winnings across all participants ($t(45) = 3.92$, $p < .001$). There was no significant difference based on SOGS score ($t(44) = 0.78$, ns). Even under simplified conditions with equal payouts for every win, participants showed a similar underestimation bias as previously found, with a mean estimation of their bank at £3.75 compared to the actual value of £4.90.

Frequency and Streak Estimation Similarly, participants underestimated the number of wins experienced during the sequence, both in total and in streaks. The mean estimation of wins was 15.40, across all conditions, compared to the actual 23 wins ($t(46) = 11.18$, $p < .001$). The mean estimation of the streak in the "peak" streak conditions was 5.52, compared to the actual 9 wins ($t(23) = 10.64$, $p < .001$). This strong inaccuracy of frequency judgments in the same direction as the total winnings estimation indicates that memory may play a key role in evaluations and that participants are not likely to be automatically encoding frequencies during the task (Haberstroh & Betsch, 2002).

Summary The third experiment suggests limitations of the strong peak-end effect that had been found initially and implies sensitivity to value and strings of losses. For example, participants informally reported streaks of 30 pence wins as less affectively exciting than high-value "jackpot" wins, especially when experienced alongside long strings of non-wins (a necessary consequence of controlling the number of wins across conditions). In line with Gilovich (1983) hypotheses of post-gambling behavior, participants seemed to focus on the "losses" from the sequence when reporting about their experience. And in this simplified win/non-win condition, we again found the underestimation of total session winnings and saw this extend to frequency estimations as well. These results support a memory-based strategy for retrospective evaluations.

General Discussion

In this study we explored retrospective evaluations of temporally extended gambling episodes, focusing on estimations and choices between experiences. In examining these issues in the new domain of monetary sequences, we tested the boundaries and limitations of the peak-end rule found in previous research and explored the basic cognitive processes of frequency and sum estimations.

The main results of these experiments demonstrate that the peak-end rule extends to monetary sequences of gains, and indicate that this extension is linked to the affect or value associated with the numbers. Unlike previous experiments that used sensory stimuli without an accompanying objective scale, the point and money value stimuli used here lend themselves to aggregative rules and arithmetic calculations. Despite the availability of these simple rules, the affective saliency of peak and end values—when accentuated with high values—seems to act as an easy cue and drive retrospective evaluations. Experiment 3 showed that high monetary peaks alone may be insufficient (participants did recognize the presence of a peak streak of wins but this did not influence their evaluations). Without heightened affect to accompany the peak value, the peak-end effect may disappear. Ongoing research is examining the separate effects of affect and numerical magnitude and how the peak-end rule handles affectively-heterogeneous stimuli with positive and negative peaks. Further evidence is also needed to determine whether peak-end values are good predictors of remembered utility in subsequent decision making.

These experiments also reveal significant underestimation of sums and frequencies of numbers presented in a sequence over time. Participants did not use the simple arithmetic strategies typically used in addition or estimation tasks; however, given that estimations for sums of compared sessions reflected actual differences between those sessions, it seems likely that participants did use a strategy of some kind. Coupled with the inaccuracy of the absolute judgments, this study suggests participants may have been using a memory-based strategy for evaluations and consequently were susceptible to errors in processing and retrieval. Despite the real-world relevance of the cognitive process of estimation, there is little existing literature studying this issue and our results point to the need for future attention to this area.

While these experiments did control for likely alternative models of estimation, a confounding variance factor could not be controlled. Compared sessions differed in payout variance because the high peak-end values within a session were compensated with many low values to control the total payouts and frequency of wins. Participants in these sessions experienced longer strings of non-wins or more low payouts. However, there is evidence that the present study's findings are robust. Alba, Mela, Shimp, and Urbany (1999) concluded that, while variance cues may impact estimations in certain conditions, simple data conditions (e.g., simple, clearly-defined distribution of values) weakened the bias and strengthened other cues such as depth (e.g., magnitude).

In the context of gambling judgments and decisions, these findings depict a dangerous picture for gamblers. Evidence from this study suggests that these biased memories may further translate to suboptimal decisions—choosing to continue gambling despite losses. In gambles with variable but clearly-defined outcomes (as with the highly popular fruit machine and betting forms), people may be using the peak-end rule, making positive memories out of losing gambling experiences; flashes, sounds and excitement focused on the peak win may exploit this bias and lead to a more extreme effect. The time spent gambling and even the overall amount of money played and lost might be forgotten in favor of the powerful memory of a big hand or jackpot win. Our memories of our experiences—colonoscopies, films, trips to the casino or otherwise—may not be quite as dependable as we would like to think.

Acknowledgments

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