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ORIGINAL PAPER

Implicit Valuation of the Near-Miss is Dependent on Outcome Context

Parker J. Banks[1,2] · Matthew S. Tata[1] · Patrick J. Bennett[2] · Allison B. Sekuler[2] · Aaron J. Gruber[1]

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Abstract Gambling studies have described a "near-miss effect" wherein the experience of almost winning increases gambling persistence. The near-miss has been proposed to inflate the value of preceding actions through its perceptual similarity to wins. We demonstrate here, however, that it acts as a conditioned stimulus to positively or negatively influence valuation, dependent on reward expectation and cognitive engagement. When subjects are asked to choose between two simulated slot machines, near-misses increase valuation of machines with a low payout rate, whereas they decrease valuation of high payout machines. This contextual effect impairs decisions and persists regardless of manipulations to outcome feedback or financial incentive provided for good performance. It is consistent with proposals that near-misses cause frustration when wins are expected, and we propose that it increases choice stochasticity and overrides avoidance of low-valued options. Intriguingly, the near-miss effect disappears when subjects are required to explicitly value machines by placing bets, rather than choosing between them. We propose that this task increases cognitive engagement and recruits participation of brain regions involved in cognitive processing, causing inhibition of otherwise dominant systems of decision-making. Our results reveal that only implicit, rather than explicit strategies of decision-making are affected by near-misses, and that the brain can fluidly shift between these strategies according to task demands.

Keywords Gambling · Near-miss · Reinforcement learning · Expectation · Arousal

✉ Aaron J. Gruber
aaron.gruber@uleth.ca

1 Department of Neuroscience, University of Lethbridge, EP 1219, 4401 University Drive W, Lethbridge, AB T1K 6T5, Canada

2 Vision and Cognitive Neuroscience Lab, Department of Psychology, Neuroscience, and Behaviour, McMaster University, Hamilton, ON, Canada

Introduction

Many of the worlds 7.7 million gaming machines (Ziolkowski 2016) intentionally present a high number of near-miss outcomes (Harrigan 2008). In the Canadian province of Ontario, for example, slot machines are legally permitted to exhibit near-misses at a rate twelve times above chance (AGCO 2014). Near-misses are outcomes that result in no reward or financial payout, yet appear proximally close to a win. In many activities, such as bowling, nearly missing an optimal outcome (a strike) is an informative indicator of performance that is useful for improvement. In games of chance however, near wins are no more informative than losses. Nonetheless, they have significant effects on gambling behaviour, such as increasing the time spent gambling (Côté et al. 2003; Kassinove and Schare 2001).

Near-misses are reported as more similar to a win than to a full loss in some studies (Dixon et al. 2011), but also as less pleasant than full misses in others (Strickland and Grote 1967). Reid (1986) provides two explanations to reconcile these apparently discrepant reports. First, the near-miss may induce frustration when expected outcomes are violated, strengthening ongoing behaviour in a way similar to a win (Amsel 1958). Dixon et al. (2011) support this theory, finding that near-misses evoke physiological reactions indicative of frustration to a greater extent than do wins or losses (Otis and Ley 1993; Osumi and Ohira 2009). Second, symbols indicating reward become conditioned reinforcers, so their presentation in near-misses have a reinforcing effect that promotes persistence (Skinner 1953). For example, Wohl and Enzle (2003) demonstrate that modest payouts following near losses increase the perception of personal luck and increase subsequent bet sizes, whereas identical payouts after missing much larger wins have the opposite effect. Therefore, the near-miss may act as a contextually dependent conditioned stimulus (CS) that is pleasing in negative contexts (relieves expected losses), but is frustrating in positive contexts (subverts expected wins).

We first investigated how reward, attention, and feedback influence the near-miss effect in a choice task among two simulated gambling machines. One machine had a net positive payout, while the other was negative. We found that choice stochasticity and the ability to avoid machines with negative expected returns was the primary determinant of performance in the task. Furthermore, the near-miss effect on machine valuation depended on reward expectation. Near-misses were valued more than losses on the negative payout machine, but less than losses on the machine with a positive expected return. We replicate this contextual effect, also finding that it is robust against changes to payment and performance feedback.

These first experiments failed to address whether the near-miss affects explicit choice valuation or implicit biases (Guillaume et al. 2009). However, imaging studies have revealed neural correlates of the near-miss in the insula, ventral striatum, and it's dopaminergic inputs from the substantia nigra (SNr) and ventral tegmental area (VTA) (Clark et al. 2009; Chase and Clark 2010; Clark et al. 2014; Habib and Dixon 2010). Given that these brain structures mediate valuation, motivation, habits, and sensorimotor control of choices, we expect that implicit choice mechanisms are at play (Yin and Knowlton 2006; Graybiel 2008; Jog et al. 1999; Yu et al. 2010). In contrast, cognitive systems such as the medial prefrontal cortex (mPFC) and orbitofrontal PFC (OFC) do not respond to the near-miss (Clark et al. 2014; van Holst et al. 2014), but instead inhibit sensorimotor control over behaviour (O'Doherty et al. 2004; Jahanshahi et al. 2000; Knoch et al. 2005). These regions are also sensitive to the size of received rewards and punishments (O'Doherty et al. 2001), suggesting a role in explicit valuation of choices. Furthermore, reducing perceived control over gambling choices (Langer 1975) activates the OFC, while reducing activity in the dorsal striatum, dorsal anterior cingulate cortex (ACC), and rostral ACC following rewards and near-misses (Walton et al. 2004; Tricomi et al. 2004; Clark et al. 2009). Therefore, we hypothesize that recruitment of cognitive systems through reduced choice control and explicit valuation of choices suppresses habitual behaviour, mitigating the near-miss effect.

To test this hypothesis, we investigated whether the contextual near-miss effect persists when placing bets on, rather than choosing between, gambling machines. We found that near-misses are valued no differently than losses in this task, regardless of reward expectation. Near-miss proportions also no longer affect discrimination between the two gambling machines. Instead, near-misses influenced the valuation of all choices, suggesting that the near-miss acts on arousal, rather than choice valuation.

Methods

Experiments 1 & 2: Binary Choice Task

The behavioural task was programmed in VB.NET using a Windows computer. It was presented on a touchscreen tablet with a 10.6″ monitor. The task display consisted of two simulated electronic gaming machines, each activated by distinct buttons (Fig. 1). Pressing either button would cause three reels in the associated machine to randomly iterate through five distinct images of fruit at different rates for 3.36 s before simultaneously stopping and displaying an outcome. Winning outcomes were displayed as three matching fruit icons followed by a dialog box stating that 10 credits had been won. Losing outcomes consisted of three non-matching icons followed by a message that 10 credits had been lost. Near-misses were identical to losses except that they were displayed as two identical icons followed by a third mismatch. In Experiment 1, the cumulative total of credits was updated after each trial and displayed at the top of the screen. However, in Experiment 2 this counter was removed for half of the subjects, in order to reduce outcome feedback.

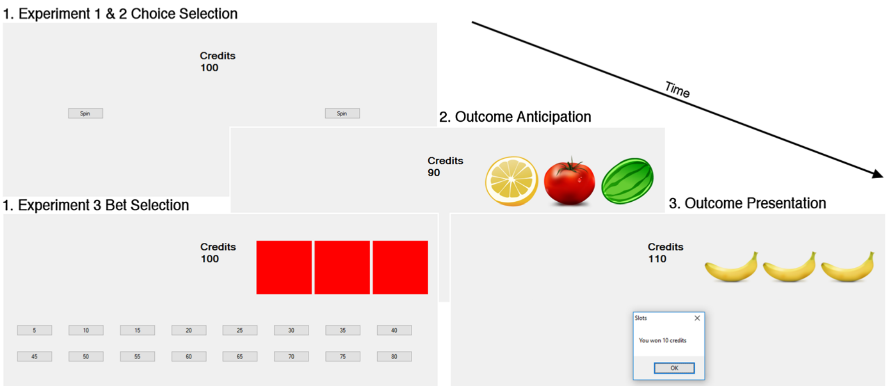

Fig. 1 Timeline of trials in Experiments 1–3. In Experiments 1 & 2 (*top left*) participants chose between two simultaneously presented slot machines. In Experiment 3 (*bottom left*) a machine was randomly chosen and highlighted in *red*. Participants were given 16 bets to choose between. The outcome anticipation (*middle*) and outcome presentation (*right*) stages were the same between all experiments (Color figure online)

During the course of the experiment, one machine would be "hot" (60% of trials were wins) and the other "cold" (40% of trials were wins). Additionally, each machine could be "balanced" or "unbalanced" such that they would have a respective 1/3 or 2/3 probability of presenting a near-miss instead of a loss. These probabilities remained constant throughout the task.

Experiment 3: Value Judgement Task

The task consisted of two simulated electronic gaming machines visible on one screen, as in Experiments 1 & 2 (Fig. 1). However, to reduce control over choices and inhibit habitual, sensorimotor responding, the machine to be played was randomly selected by the computer on each trial and highlighted in red. The participant was then required to place bets in values ranging from 5 to 80 points in 5 point increments by pressing one of 16 values displayed on the bottom of the screen. A minimum value of 5, rather than 0 points was selected to prevent subjects from adopting a default strategy of avoiding decisions, and ensure all experienced outcomes were wins or losses. The bet procedure was identical for either selected machine. After the bet was selected, the highlighted machine would spin and display an outcome as in Experiment 1. On a loss or near-miss outcome, the amount bet would be subtracted from the subject's total credits, while on a win, twice the bet amount would be returned. All other features of the task were identical to that used in Experiment 1.

Participants

One hundred ninety-two undergraduates from the University of Lethbridge, McMaster University, and members of the greater community participated in the study (50 males, mean age = 19.40, SD = 3.76). Sixty-four subjects participated in Experiment 1 either as a volunteer or in return for course credit. Ninety-six participated in Experiment 2, in exchange for either course credit (n=48) or course credit and payment of $10 (n=48). Participants were assigned to one of four groups of twenty-four participants each in a feedback × payment design. Thirty-two participated in Experiment 3 in exchange for pay and course credit in psychology.

Procedure

All procedures and experimental tasks were approved by the University of Lethbridge Human Subjects Review Committee and the McMaster University Research Ethics Board. After providing informed consent, subjects completed one of the three experimental tasks using a provided touchscreen pen. They were given a starting balance of 100 credits and instructed to use the two machines to gain as many credits as possible. In Experiment 2, paid participants were also informed that their payment was conditional upon reaching a certain undisclosed score and that failure to reach this score by the end of the experiment would result in no payment. These instructions were a deception, designed to ensure maximal attention to the task. At the end of the experiment, all paid participants were informed of this deception and paid in full, regardless of task performance. Subjects in Experiment 3 were instructed to use the 16 bet options to gain points, altering their bets in response to the machine selected by the computer.

Subjects were also requested to refrain from stereotypical behaviours (i.e., selecting a single machine, alternating between machines each trial) and informed to continue playing should the counter become negative. No other direction was given. Once 350 trials were completed, a screen indicating the final score was displayed.

After task completion, subjects were screened with the Problem Gambling Severity Index (Ferris and Wynne 2001), CAMH Gambling Screen, World Health Organization ASSIST v3.0, and an additional demographic questionnaire. Those indicating ADD/ADHD diagnoses, a history of problem gambling behaviour, or substance abuse were eliminated from the study and replaced with additional participants. Seven subjects were replaced using these criteria. An additional subject was removed from Experiment 3 for betting 5 points on all 350 trials.

Computational Modeling

Subjects' responses in Experiments 1 & 2 were coded as a "1" or "0" depending on whether the hot or cold machine was selected. Choice data was fit to a stochastic variant of the Q-Learning model (Sutton and Barto 1998), as described by Daunizeau et al. (2014):

$$Q_{t+1} = Q_t + \alpha_{t+1}(r_{t+1} - Q_t). \tag{1}$$

This model (Eq. 1) allows for estimation of how choices and experienced outcomes influence internal value estimations of the hot (Q^H) and cold (Q^C) machines using a dynamic learning rate (α_t). In particular, these changes in valuation are updated by the prediction error signal ($r_{t+1} - Q_t$) that represents the difference between current outcomes and expected rewards. This signal is strongly correlated with the firing of midbrain dopamine neurons (Holroyd and Coles 2002; Bayer and Glimcher 2005) making it of particular relevance to human decision-making. Furthermore, the learning rate represents how much of an influence current reward (r_t) has on the future estimated value of the action (Q_{t+1}).

The probability of selecting the hot and cold machines ($M^i, i \in [H, C]$) was determined using the softmax equation parameterized by the inverse temperature (β):

$$P_t(M^i) = \frac{exp\beta Q_t^i}{\sum_j exp\beta Q_t^j}, \tag{2}$$

where β controls the tradeoff between exploitation and exploration of available actions. A high β increases the probability of selecting the most highly valued option, while a low value makes choices more stochastic. In the context of the present experimental task, a high β is ideal because reward probabilities remain constant throughout the task. Rather than independently estimating hidden states on each trial, values at each trial t were updated according to the posterior density estimates for states at trials 1 to $t + k$ using a Kalman filter (Daunizeau et al. 2009). The use of the forward-pass lag k (set to 16 trials) allows for observation of how changes in hidden states at trial t influence future hidden states and helps to smooth hidden state estimates. Choice performance (% hot choices) was averaged over 7 blocks of 50 trials for each subject. For computing the correlations between choice performance, Q^H, Q^C, α, and β, single values were independently estimated for each subject, averaged across all trials.

To determine how outcomes changed valuation of the hot and cold machines (i.e., hidden state values), we performed a Volterra decomposition of Q^H and Q^C values for each trial onto four basis functions: previous choice (P.C.), loss, near-miss, and win, according to Eq. 3:

$$x_t = \omega^0 + \sum_{\tau} \omega_{\tau}^1 u_{t-\tau} + \sum_{\tau_1} \sum_{\tau_2} \omega_{\tau_1,\tau_2}^2 u_{t-\tau_1} u_{t-\tau_2} + \ldots \tag{3}$$

Volterra modelling allows for observation of input response characteristics of non-linear systems as Volterra weights (Boyd et al. 1984). At each trial t the Volterra weight x is estimated from inputs u over trials t to a lag of τ (set to 16 trials) using a series of Volterra kernels ω. The first kernel ω^1 represents the linear transformation of lagged input basis functions into the output, ω^2 represents the effect of past inputs being dependent on other earlier inputs, and so on. As with prediction error, these weights provide a measure of how subjects' valuation of each machine change from baseline in response to past choices and outcomes. The benefit of Volterra modelling over analysis of raw prediction error is that the effect of current and past inputs on hidden state responses can be estimated, and inputs can be orthogonalized so that the effect of one input (e.g., wins) is computed independently of all other inputs (e.g., previous choice). Inputs were ordered so that the effect of previous choice on hidden states was subtracted from that of wins, near-misses, and losses during orthogonalization. To control for trial order effects, we also detrended inputs prior to decomposition.

All models were implemented in Matlab using the VBA toolbox. All statistical analyses were performed in R.

Results

Experiment 1

Stochasticity and Cold Machine Valuation (Q^C) Drive Choice Discrimination

We compared the effects of hot machine valuation (Q^H), cold machine valuation (Q^C), learning rate (α), and choice stochasticity (β) on choice performance by fitting each subject's choice data to the reinforcement learning model (Eqs. 1, 2). Correlations between performance and parameter estimates for all participants (Fig. 2) show that performance increases with decreasing valuation of the cold machine (Q^C) [$r(62) = -.670, p < .001$], or with increasing exploitation (β) [$r(62) = .625, p < .001$]. In contrast, Q^H [$r(62) = .184, p = .147$] and α [$r(62) = -.242, p = .054$] contribute relatively little to performance. Q^C also increases as β decreases [$r(62) = -.645, p < .001$]. Therefore, choice performance is primarily determined by how well subjects can inhibit valuation of the cold machine and increase exploitation.

A 2 (Hot Balanced/Unbalanced) $\times$ 2 (Cold Balanced/Unbalanced) ANOVA, using orthogonal contrasts, was applied to choice performance data, collapsed across trial blocks. While there was no main effect of unbalancing either the hot or cold machines on performance, there was a significant interaction [$F(1, 444) = 12.132, p < .001$] such that performance is increased in the both-balanced and both-unbalanced conditions, relative to when only the hot or cold machine is unbalanced (Table 1). Therefore, choice discrimination is influenced by differences in near-miss proportions between choice options, rather than the overall proportion of near-misses encountered. Given (*i*) the strong correlations between performance and Q^C or β and performance, and (*ii*) evidence that the near-miss

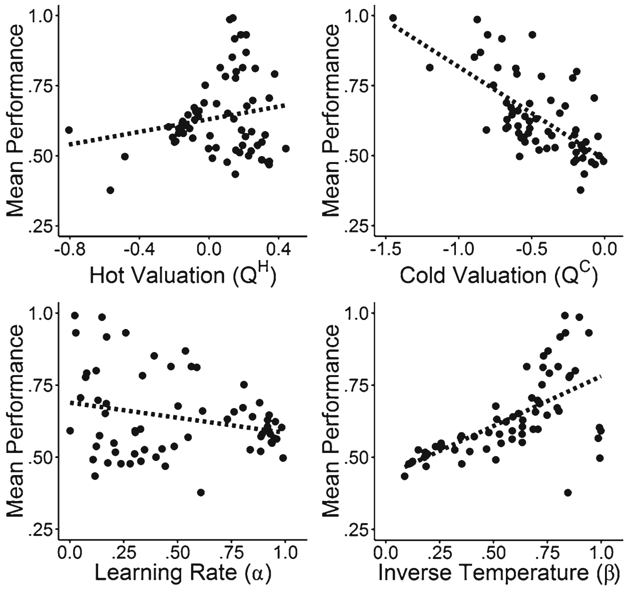

Fig. 2 Correlation of choice performance and mean Q^H, Q^C, α, or β in Experiment 1

Table 1 Performance and persistence following wins (P.W.), near-misses (P.N.), and losses (P.L.) by unbalancing condition in Experiment 1, and by payment and feedback in Experiment 2

	Experiment 1				Experiment 2			
	H_BC_B	H_UC_B	H_BC_U	H_UC_U	No Feedback		Feedback	
					Unpaid	Paid	Unpaid	Paid
Perf	.66 (.02)	.60 (.01)	.62 (.02)	.68 (.02)	.62 (.01)	.59 (.01)	.60 (.01)	.60 (.01)
P.W.	.81 (.03)	.72 (.03)	.78 (.03)	.73 (.03)	.81 (.02)	.68 (.02)	.79 (.02)	.74 (.02)
P.N.	.60 (.03)	.46 (.03)	.61 (.03)	.71 (.02)	.52 (.02)	.54 (.02)	.56 (.02)	.60 (.02)
P.L.	.56 (.03)	.43 (.03)	.58 (.03)	.64 (.03)	.44 (.02)	.51 (.02)	.53 (.02)	.59 (.02)

SEM in parentheses

increases arousal (Clark et al. 2012; Dixon et al. 2011; Osumi and Ohira 2009), we suggest that differing near-miss proportions increases choice stochasticity through arousal, a potential indicator of frustration. This arousal may prevent inhibition of the cold machine choice (or nullify the difference in Q among actions) and thereby reduce discrimination.

Because the sensorimotor system has been shown to drive rapid response shifting following losses (Skelin et al. 2014), we next investigated the probability of choosing the same machine on subsequent trials (persistence) after a win, near-miss, or loss. As seen in Table 1, persistence following wins decreases when the hot machine is unbalanced $[F(1, 444) = 5.984, p = .015]$. Furthermore, persistence increases following losses $[F(1, 444) = 17.568, p < .001]$ and near-misses $[F(1, 444) = 25.276, p < .001]$ when the cold machine is unbalanced. A hot × cold interaction with near-misses also influences persistence following losses [$F(1,444) = 11.502, p < .001$] and near-misses [$F(1,444) = 21.895, p < .001$], in a manner analogous to that seen in performance.

The Near-Miss Effect is Dependent upon Context of Reward Expectancy

To determine the effect of the near-miss on outcome valuation, Volterra decompositions of immediate changes in hidden states by losses, near-misses, wins, and previous choice as basis functions were analyzed with two one-way ANOVAs. There was a significant main effect of input basis on Q^H [$F(3,252) = 9.494, p < .001$] and Q^C [$F(3,252) = 24.210, p < 001$]. Near-misses tended to decrease valuation of the hot machine from baseline ($M = .03, SE = .02$) relative to losses ($M = .11, SE$=.05) [$t(126) = -1.455, p = .148$] (Fig. 3). Conversely, they tended to increase cold machine valuation ($M = -.04, SE$=.02) relative to losses ($M = -.12, SE$=.04), [$t(126) = 1.781, p = .077$]. These effects fell short of statistical significance, and therefore provide only weak evidence that the effect of the near-miss is contextual. In negative utility conditions (cold machine), it increases valuation, while in positive utility conditions (hot machine) it reduces valuation. We show much stronger evidence of this effect in Experiment 2.

Because near-miss proportions may change the extent to which near-misses differ from losses, we conducted 2 (Hot Balanced/Unbalanced) × 2 (Cold Balanced/Unbalanced) ANOVAs to assess the difference between near-miss and loss associated prediction error. As seen in Fig. 3, unbalancing the hot machine increased Q^C values following near-misses relative to losses ($M = .145, SE = .043$) compared to balanced ($M = .026, SE = .040$) [$F(1,60) = 4.057, p = .049$]. Unbalancing the hot machine also reduced relative Q^H response to near-misses ($M = -.131, SE = .044$) compared to balanced

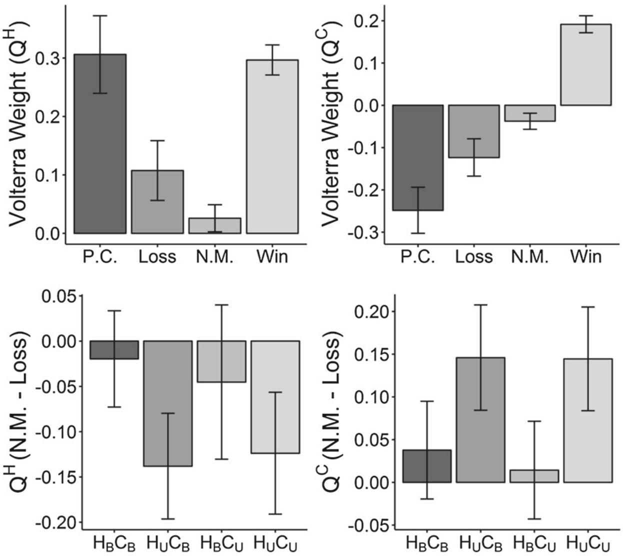

Fig. 3 Effect of previous choice and reinforcement outcome on Volterra weights for Q^H and Q^C in Experiment 1 (*top*). Difference between near-miss and loss associated Volterra weights for each balancing condition (*bottom*): Hot balanced/unbalanced (H_B/H_U); Cold balanced/unbalanced (C_B/C_U). SEM in *error bars*

($M = -.032, SE = .049$), but this difference was not significant [$F(1, 60) = 2.153, p = .148$]. However, increasing near-miss proportions on the hot machine seemed to increase the contextual effect of the near-miss on both machines. Similar ANOVAs on prediction error differences between wins and losses found no effects of unbalancing conditions on changes in Q^H or Q^C ($F < 2.169, p > .145$ in each case).

Experiment 2

Performance is Unaffected by Payment or Feedback

As in Experiment 1, the strong correlation among performance and Q^C [$r(94) = -.510, p < .001$] and β [$r(94) = .706, p < .001$] provide confirmatory evidence that performance is primarily determined by how well subjects can learn to reduce valuation of the cold machine and focus on choice exploitation, rather than exploration (Table 1, Fig. 4). A moderate correlation between Q^C and β [$r(94) = -.429, p < .001$] was also found, indicating that valuation of the cold machine and inverse temperature act semi-dependently on discrimination. Again, the correlation between performance and Q^H [$r(94) = .132, p = .200$] or α [$r(94) = -.196, p = .056$] was weak, confirming that valuation of the hot machine and learning rate are not highly relevant to performance.

As seen in Table 1, a 2 (Paid/Unpaid) × 2 (Feedback/No Feedback) ANOVA collapsing over trial block and unbalancing conditions, indicated no significant effects of payment or feedback on performance ($F < 2.632, p > .104$ in each case). However, payment does significantly decrease persistence after wins [$F(1, 668) = 21.619, p < .001$] and increase it following losses [$F(1, 668) = 9.326, p = .002$], but has no effect of behaviour following near-misses. Provision of feedback also increases persistence following near-misses [$F(1, 668) = 4.451, p = .035$] and losses [$F(1, 668) = 18.152, p < .001$], but does not after

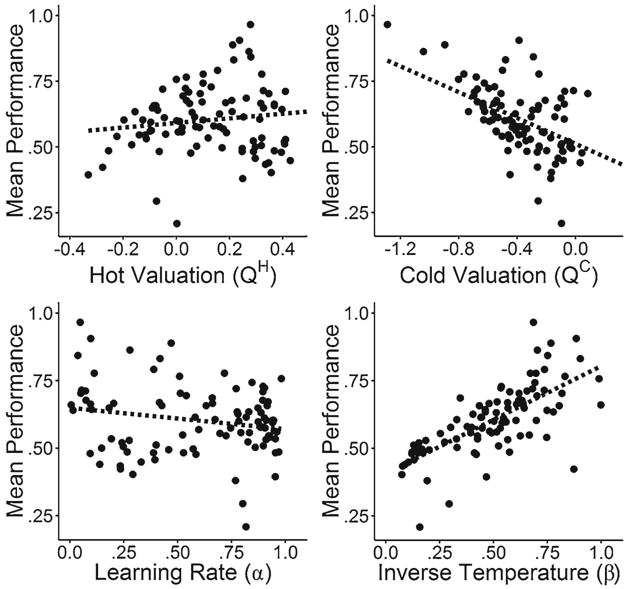

Fig. 4 Correlation of choice performance and mean Q^H, Q^C, α, or β in Experiment 2

wins. Regardless, our finding that the effects of Q^C and β on performance are replicable across payment and feedback conditions provide strong support for our conclusion that performance is driven by choice exploitation and low valuation of the cold machine.

Contextual Effect of the Near-Miss is Independent of Payment and Feedback

Volterra decompositions of hidden states again indicated there was a significant effect of input basis on Q^H $[F(3,380) = 13.057, p < .001]$ and Q^C values $[F(3,380) = 52.284, p < .001]$. As shown in Fig. 5, near-misses ($M = .06, SE = .02$) were valued less than losses ($M = .18, SE$=.04) on the hot machine $[t(190) = -2.583, p = .011]$, but near-misses ($M = -.06, SE$=.02) were valued more than losses ($M = -.17, SE$=.03) on the cold machine $[t(190) = 2.694, p = .008]$. These results are consistent with those of Experiment 1 and have greater statistical power. This replication with different University populations provides strong evidence that the influence of the near-miss is dependent on outcome context. Further segregation of hidden state responses by payment and feedback conditions revealed no significant effects of these treatments on change in Q^H or Q^C following previous choice, loss, near-miss, or win outcomes ($F < 2.233, p > .138$ in each case). Therefore, the contextual effect of the near-miss is robust against differences in payment or outcome feedback, despite their effects on choice persistence.

The modulatory effect of unbalancing condition on near-miss valuation was the same as in Experiment 1 when collapsed over payment and feedback conditions. As shown in Fig. 5, Q^C sensitivity to near-misses was again increased relative to losses when the hot machine was unbalanced ($M = .182, SE = .039$), compared to the balanced condition ($M = .040, SE = .032$) $[F(1,92) = 7.942, p = .006]$. Unbalancing the hot machine significantly decreased relative change in Q^H following near-misses ($M = -.186, SE = .041$)

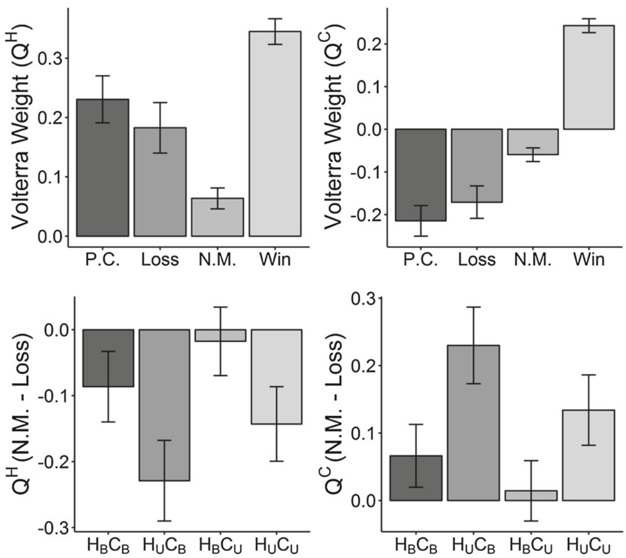

Fig. 5 Effect of previous choice and reinforcement outcome on Volterra weights for Q^H and Q^C in Experiment 2 (*top*). Difference between near-miss and loss associated Volterra weights for each balancing condition (*bottom*). Acronyms as in Fig. 2. SEM in *error bars*

compared to balanced ($M = -.052, SE = .037$) [$F(1, 92) = 5.744, p = .019$]. As in Experiment 1, there was no effect of balancing condition on change in Q^H or Q^C following wins, relative to losses ($F < 1.277, p > .260$ in each case). The difference between wins or near-misses, relative to losses, was similarly unaffected by payment or feedback conditions ($F < 1.728, p > .191$ in each case).

One concern is that the contextual effect of the near-miss may result from the differences in the proportions of losses and near-misses experienced, rather than outcome valuation. However, on the cold machine 28.80 and 28.40% of experienced outcomes were losses and near-misses respectively. On the hot machine, 16.91 and 17.42% of outcomes were losses and near-misses. These proportions did not differ ($\chi^2 < 1.849, p > .174$ in each case), so the observed effects are most likely due to a difference in outcome valuation.

Experiment 3

Bet Performance

The effects of machine selected and unbalancing conditions on bet amount were tested via a 2 (Hot Balanced/Unbalanced) × 2 (Cold Balanced/Unbalanced) × 2 (Hot/Cold machine selected) ANOVA, collapsed across trial block. The average bet size when either the hot or cold machines were unbalanced [H_UC_B ($M = 38.82, SE = 1.57$), H_BC_U ($M = 34.36, SE = 1.63$)] was significantly higher than when both machines were balanced or unbalanced [H_BC_B ($M = 22.83, SE = 1.04$), H_UC_U ($M = 25.02, SE = 1.05$)], as indicated by significant effect of unbalancing the hot machine [$F(1, 612) = 7.766, p = .005$] and a hot × cold interaction [$F(1, 612) = 90.346, p < .001$] (Fig. 6). There was also a significant effect of machine selected on bet size [$F(1, 612) = 4.516, p = .034$], but no machine × unbalancing condition interactions, suggesting that discrimination was not

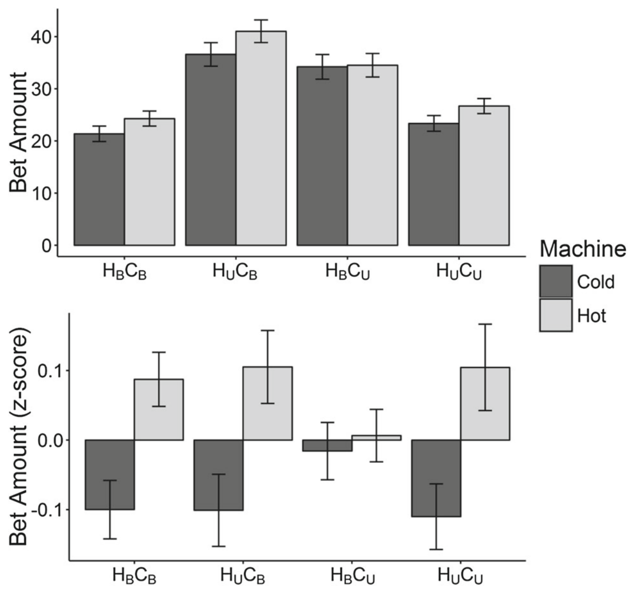

Fig. 6 Effect of unbalancing condition on bet size for the hot and cold machines in Experiment 3. SEM in *error bars*

influenced by the added near-misses. However, some participants might not utilize all available bet size options, but select between a limited number (e.g., bets < 40 credits) even though they could discriminate among hot and cold machines. To correct for this possibility, bet data were individually transformed into z-scores for each participant, before averaging into ten trial blocks. As seen in Fig. 6, a second ANOVA again found that bets on the hot machine ($M = .08, SE = .02$) were significantly larger than those on the cold ($M = -.08, SE = .02$) [$F(1, 612) = 22.898, p < .001$]. While the $H_B C_U$ condition did seem to exhibit reduced discrimination, there were no effects of hot or cold balance, or a hot × cold interaction ($F < 2.186, p > .139$ in each case). Therefore, near-miss proportions influenced bets made towards both machines, but not discrimination between them, when subjects were asked to explicitly value choice options.

To determine whether the near-miss still had a contextual effect, a 2 (current choice) × 2 (previous choice) × 3 (previous outcome) ANOVA was conducted on bet data. There was no effect of previous machine selected on current bet size [$F(1, 360) = .013, p = .910$] (Fig. 7). Current machine selected also had no effect on bet size [$F(1, 360) = 1.651, p = .200$]. However, previous outcome significantly affected bet size [$F(2, 360) = 6.515, p = .002$] as bets following wins (M=27.002, SE=1.463) were significantly lower than those following near-misses ($M = 34.673, SE = 1.726$) [$t(246) = -3.390, p < .001$] and losses ($M = 33.910, SE = 1.718$) [$t(246) = -3.061, p = .002$]. However, near-misses were not different from losses [$t(246) = .313, p = .755$], indicating that the contextual effect of the near-miss was eliminated. No significant interactions were observed.

Discussion

The purpose of our study was to compare the valuation of near-misses to losses and wins in both winning and losing contexts. We have demonstrated that the effect of the near-miss on choice depends on the context of reward expectation. The near-miss is more negatively valued than losses in winning contexts, but it is more positively valued than full losses in losing contexts. In other words, when participants selected a machine associated with a high expectation of winning, near-misses violated this expectation and were registered more negatively than normal losses. However, when participants chose the losing machine, near-misses subverted otherwise expected losses, causing them to be more positively valued than losses. This contextual effect on choice is driven by outcome exploitation and reduced valuation of the cold machine, and is influenced by differences in near-miss

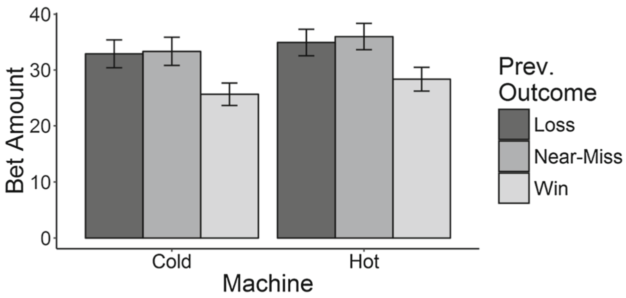

Fig. 7 Effect of outcome on bets towards the hot and cold machines in Experiment 3. SEM in *error bars*

proportions between machines. However, engagement of cognitive systems needed to generate bet sizes suppresses the effect of the near-miss on discrimination.

Past research has focused on how the near-miss influences persistence towards a single choice option. This research has led to contrasting reports of whether the near-miss is positively or negatively valued. By employing a dual choice design we have shown that the near-miss can negatively or positively influence choices. Our analysis was aided by a computational reinforcement learning model, which have been very useful for studying decision making (Balleine and O'Doherty 2010; Ito and Doya 2009). Volterra decomposition of hidden states provides a measure similar to raw prediction error, but is more informative because it can reveal orthogonalized impulse responses to outcomes, both current and past (Daunizeau et al. 2014). This analysis allowed us to investigate whether Q^H, Q^C, or stochasticity could best account for performance, and which were most affected by near-misses. When reward expectation is low, such as on the cold machine, near-misses are more highly valued than losses. However, when reward expectation is high, near-misses are more negatively valued than losses. This contextual effect provides strong support for the frustration theory of Amsel (1958). In high reward contexts, failure to reach expected wins induces frustration, while near-misses reduce frustration in low reward contexts by subverting losses.

This contextual effect, which is increased by unbalancing the hot machine, also provides support for Skinner's description of the near-miss as a conditioned stimulus (Skinner 1953). Past research has demonstrated that the potency of the near-miss to affect behaviour depends on its relative occurrence, or reliability as an indicator of reward. For example, Kassinove and Schare (2001) and Kurucz and Körmendi (2012) demonstrate an inverted "U" relationship between near-miss proportions and gambling persistence; a 30% rate has a maximal effect, despite subjects being unable to distinguish sets of trials exhibiting 0 and 45% near-misses. This relationship likely results because insufficient or excessive near-misses reduce the proportion of times symbols are paired with wins, reducing their reliability as an indicator of wins. Pigeons demonstrate analogous behaviour, preferring to respond in conditions where the CS is strongly predictive of reinforcement over those where additional presentations of the CS occur without reward, despite increasing response frequency in the latter case (Schuster 1969). Thus, there appears to be a tradeoff between the frequency (reliability) of the near-miss and its invigorating effect, either via frustration or arousing effects as a CS.

Our research further highlights the relationship between the near-miss effect and how reliably it is paired with outcomes. Unbalancing the hot machine increases its contextual effect in both high and low reward contexts, suggesting that it becomes reliably paired with wins or losses. Our finding that unbalancing the cold machine does not also increase the contextual effect is puzzling, but may highlight the role of frustration, in conjunction with reliability. In winning contexts, frustration induced by near-misses may be more visceral than its alleviating effect experienced in positive contexts. Therefore, changes in proportions of positively viewed near-misses may not influence its contextual effect to the same extent changes in frustrating near-miss proportions.

Near-miss proportions influenced choice discrimination in Experiment 1 and bet size in Experiment 3, providing further evidence of its ability to evoke frustration or arousal. In Experiment 1, incongruities in near-miss proportions between the two machines, rather than number of near-misses experienced, decreased choice discrimination. In Experiment 3, different near-miss proportions increased bet sizes, without affecting discrimination. Given past research demonstrating that the near-miss increases physiological arousal, and the the strong influence of inverse temperature and valuation of the cold machine on discrimination, we posit the following: Differences in near-miss proportions increase arousal, causing choices to become more stochastic. This increased stochasticity causes the low payout (cold) machine to be selected more often, despite it having a lower internal valuation, thus decreasing performance. Our finding that bet size is increased following unpleasant outcomes such as losses and near-misses, regardless of the machine selected, provides further evidence that this increase in arousal is linked to frustration. This increase is also indicative of the gambler's fallacy, in which wins are thought to be more likely following losses (Clotfelter and Cook 1993). However, increased arousal likely accompanied this effect, given strong support from the extensive literature linking frustration, losses, and the near-miss, and our finding that changes in unbalancing conditions also increased bets, irrespective of experienced outcomes.

Our finding that valuation of the cold (rather than hot) machine was a primary determinant of choice performance highlights the different roles of approach and avoidance based systems of decision-making. McNaughton and Gray (2000) proposed that negative stimuli act on attentional systems that inhibit punishing behaviours (i.e., response inhibition). For example, pathological gamblers and drug addicts exhibit impaired response inhibition and this impairment predicts reduced performance at the Iowa gambling task (Odlaug et al. 2011; Bechara and Martin 2004; Noël et al. 2007). Negative stimuli, including gambling losses, also capture attention more effectively than wins (Yechiam and Hochman 2013) and result in greater event-related potential amplitudes (Smith et al. 2003). Conversely, positive stimuli engage systems associated with exploration and impulsivity (Pickering and Gray 2001). For example, Gupta (1990) demonstrated that highly impulsive individuals learn more effectively in response to positive reinforcers, whereas negative reinforcement is most effective on those exhibiting low impulsivity. As reward probabilities are fixed in the current study, inhibition of the cold machine is of greater utility to performance than exploration induced by the hot.

Experiments 1 and 2 relied on one of two motor actions to reveal choices, which may have relied on implicit habits driven by somatosensory systems sensitive to the near-miss (Clark et al. 2014, 2009), rather than explicit valuation of choice options. In Experiment 3 we show that the contextual near-miss effect is reduced when subjects are required to bet on, rather than chose between machines. Removing control over choices has been shown to inhibit the ACC and sensorimotor striatum (Clark et al. 2009; Walton et al. 2004; Tricomi et al. 2004), and engage cognitive systems in the prefrontal cortex (e.g., OFC) that further inhibit habitual responding (Jahanshahi et al. 2000; Knoch et al. 2005) By requiring subjects to assign a value to choice options we also encouraged reliance on explicit knowledge of choice value during decision-making (Guillaume et al. 2009), primarily through activation of the OFC, due to its role in monitoring reward value (O'Doherty et al. 2001). The increase in bet size following near-misses was not statistically different from that following losses, further indicating that the near-miss effect is reduced through greater cognitive engagement. Therefore, these data support the hypothesis that the contextual effect of the near-miss primarily acts on systems responsible for sensorimotor, rather than goal-directed, decisions.

Neither the contextual effect of the near-miss, or its modulation by near-miss proportions, are influenced by the level of payment or feedback provided to subjects. Instead, payment and feedback decrease persistence following wins and increase it following near-misses and losses. Persisting following wins and switching following losses are default strategies in rats driven by the sensorimotor striatum and nucleus accumbens, respectively (Skelin et al. 2014; Wong et al. 2016). Our finding that payment and feedback both reduce these default strategies suggests that they cause subjects to exert more executive control, but these changes do not affect overall performance. We can not completely rule out the possibility that payment and feedback may interact with near-miss proportions. These interactions would require targeted experiments and larger samples to properly analyze, and so were ignored in our study. Instead, the purpose of these experiments was to demonstrate that the contextual effect of the near-miss is robust regardless of changes in feedback or payment typically employed in laboratory studies of gambling behaviour.

The present data reconcile discrepant reports of the near-miss, demonstrating that it is both positively and negatively valued, depending on the reward context in which it is presented. By using a dual-choice design, we find that valuation of a choice is determined by rewards and near-misses presented on that machine, but also those presented on other competing choices. Therefore, future studies of gambling behaviour should consider the expected utility of competing choices, in addition to previously known factors such as expected reward, near-misses, and attention (Fleming and Dolan 2010).

The present study also demonstrates that the near-miss affects only some subsystems of the brain's choice mechanism, providing insights relevant to future research. Our finding that near-misses influence implicit, rather than explicit, choice valuation suggests the near-miss effect is specific to certain forms of gambling. For example, poker and sports betting require explicit bet size selection and may be less susceptible to near-misses than games that recruit implicit decision-making strategies (e.g., slots). We speculate that this particular near-miss effect is distinct from other effects of counterfactual outcomes, such as the tendency of individuals to be more risky in their choices after losses (Brevers et al. 2017). The contextual near-miss effect may be further amplified in habitual gamblers, as they exhibit increased reliance on implicit biases (Toneatto et al. 1997) and are more affected by near-misses. Therefore, future work should explore what forms of gambling are affected by the contextual near-miss, if this interacts with other influences of counterfactual outcomes, and whether it is further amplified among problem gamblers, particularly in games that involve implicit decision-making.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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