

Supplementary Section S1: Full demographic characteristics of sample

Self-reported gambling frequency in the initial screening survey is presented in Table S1, and demographic characteristics for participants who completed the task are presented in Table S2.

Table S1. Participants' gambling frequency in the initial screening sample ($N = 251$)

	Daily	Weekly	Monthly	Yearly	Never
N (%)	8 (3.2%)	60 (23.9%)	59 (23.5%)	63 (25.1%)	61 (24.3%)

Table S2. Participant demographics in final sample ($N = 100$)

Participant characteristics	M (SD) or N
Age	38.03 (11.55)
Gender	
Man or male	54
Woman or female	43
Gender diverse	2
Rather not say	1
Country of residence	
United Kingdom	48
Canada	22
Australia	17
United States of America	7
New Zealand	6
Level of education	
High school	30
College or university degree	51
Post-graduate university degree	17
Rather not say	2
Gambling frequency	
Daily	6
Weekly	28
Monthly	34
Yearly	15
Never	17

Supplementary Section S2: Analyses of raw emotional reactivity data

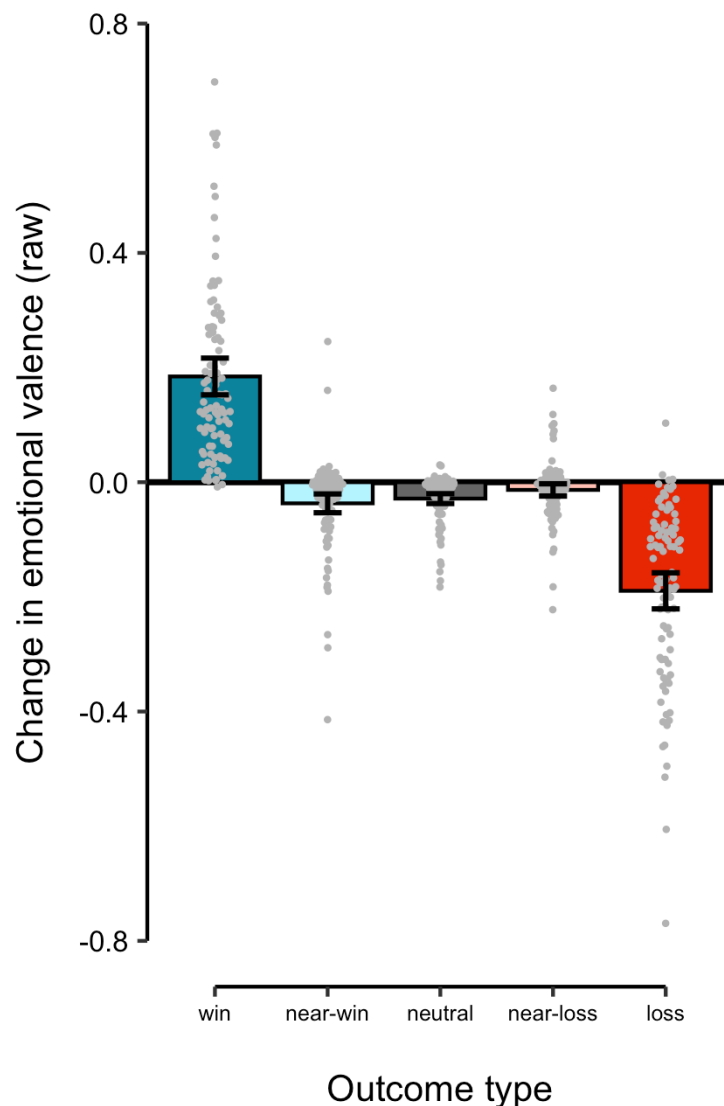


Figure S1. Mean change in emotional valence following different outcome types (positive: improvement in emotional valence; negative: deterioration in emotional valence) as measured as a proportion of the total length of the affective slider (i.e., maximum possible improvement = 1, maximum possible worsening = -1). Bars and error bars represent group-level means and 95% confidence intervals, and grey points represent data from individual participants.

Figure S1 above presents a ‘raw’ measure of emotional reactivity to each of the different outcome types, namely the pre-outcome to post-outcome change in subjective emotional reactions. As can be seen by comparison of this figure and Figure 2B in the main text, the basic pattern of effects described by the computational modelling analysis model was also evident in the raw data. However, the computational model was better able to estimate stable inter-individual differences in emotional reactivity across outcomes, and therefore had increased statistical power for PGSI moderation analyses compared with the equivalent analyses conducted on the raw data. This is evident in Figure S2 below, which analyses the raw

emotional reactivity data in a manner equivalent to Figure 3 in the main text. As can be seen by comparing Figure S2 and Figure 3, although the general direction of all effects is similar the analysis using computational model parameters has better statistical power for detecting correlations with PGSI scores. Specifically, whereas for computational modelling analyses all outcome types were associated with PGSI scores after correcting for multiple comparisons, for the raw data only emotional reactivity to wins and losses were significantly associated with PGSI scores after Bonferroni-Holm correction for multiple comparisons.

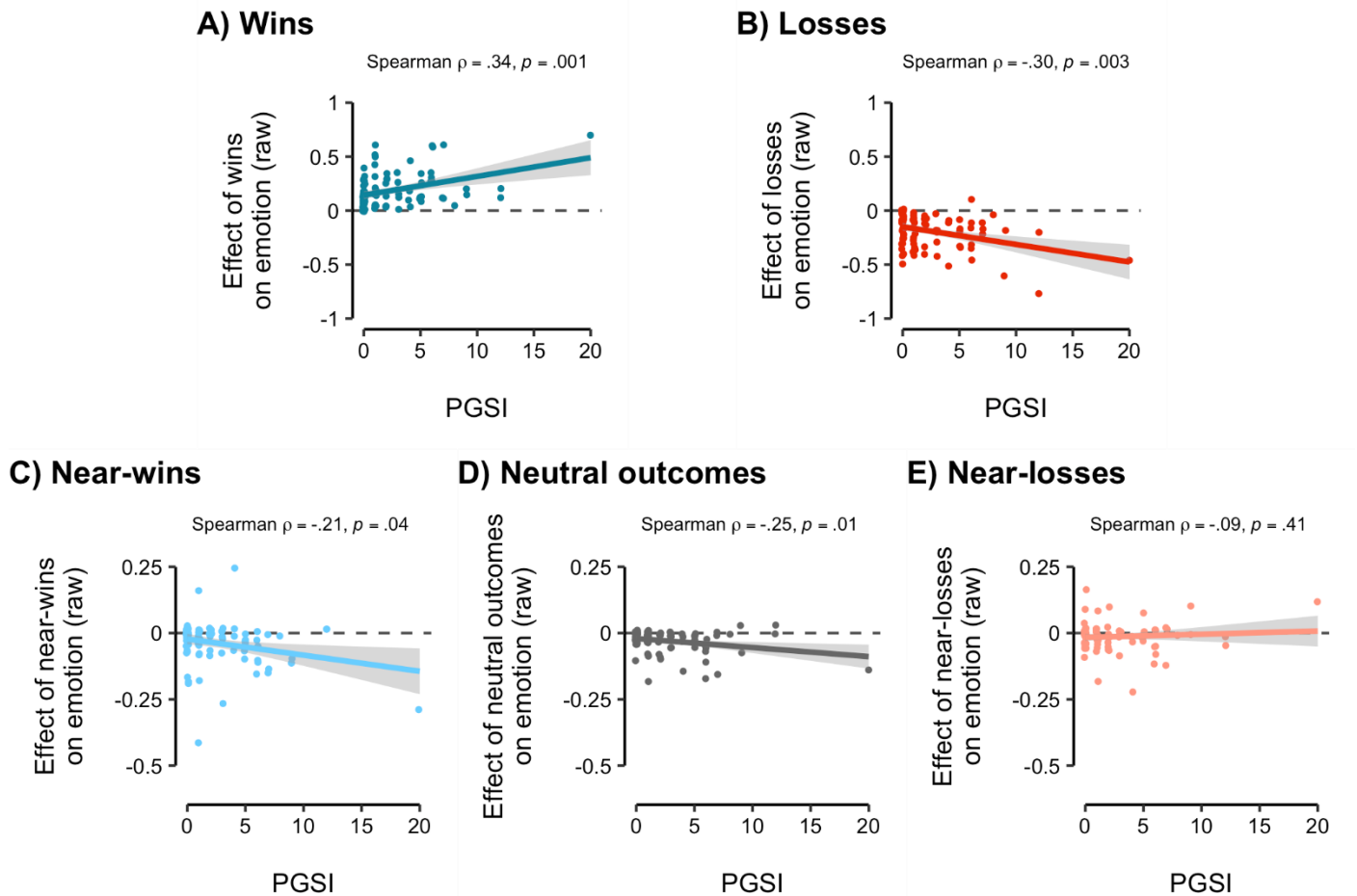


Figure S2. More severe hazardous gambling (as indicated by higher PGSI scores) was associated with greater emotional reactivity as measured by raw changes in self-reported emotional valence for all outcomes except near-losses. Positive values on the y-axes indicate more positive emotional reactions, negative values indicate more negative emotional reactions, and values of zero (horizontal dashed line) indicate no effect of a given outcome type on emotional valence. Shaded regions indicate the 95% confidence interval of the linear association between PGSI scores and emotional reactivity. Reported p -values are not corrected for multiple comparisons.

Supplementary Section S3: Additional computational modelling results

Table S3 below presents estimated correlations between the emotional reactivity parameters of the computational model for each participant. All parameters were significantly correlated with one another, suggesting that each of the parameters may have loaded on a common ‘emotional reactivity’ factor. We also found that all emotional reactivity parameters were associated with the recency-weighting parameter γ in a manner indicating that participants with more recency-weighting in the effects of previous trials (i.e., lower γ) tended to be more emotionally reactive overall. Similarly, all emotional reactivity parameters were associated with the response variance parameter ϕ in a manner indicating that participants with more unexplained variance in their emotion self-reports (i.e., lower ϕ) tended to be more emotionally reactive overall. Finally, we found that the w_0 parameter, which quantifies average emotional valence across the experiment, was significantly negatively correlated with emotional reactivity to each of the non-win outcomes in the task (losses, near-wins, near-losses, and neutral outcomes). This indicates that participants with more positive mood on average tended to experience stronger negative emotional reactions (but not stronger positive emotional reactions). We speculate that this may represent a kind of range-restriction in emotional reactions: participants who are happier to start with have more ‘room to move’ in a negative direction, and may therefore experience greater negative emotional reactions compared with participants who are initially less happy.

Table S3. Estimated correlations between computational model parameters ($N = 94$)

	w_0	w_{win}	w_{loss}	$w_{nearwin}$	$w_{nearloss}$	$w_{neutral}$	γ
w_{win}	.09	-	-	-	-	-	-
w_{loss}	-.25 *	-.87 ***	-	-	-	-	-
$w_{nearwin}$	-.34 **	-.66 ***	.77 ***	-	-	-	-
$w_{nearloss}$	-.26 *	-.44 ***	.47 ***	.77 ***	-	-	-
$w_{neutral}$	-.33 **	-.56 ***	.61 ***	.94 ***	.92 ***	-	-
γ	-.19	-.52 ***	.49 ***	.41 ***	.31 **	.37 ***	-
ϕ	-.05	-.35 **	.34 **	.26 *	.22 *	.23 *	.05

*** $p < .001$; ** $p < .01$; * $p < .05$; FDR correction for multiple comparisons.

Supplementary Section S4: Additional PGSI correlation results

As a robustness check, we investigated whether correlations between participants' PGSI scores and their emotional reactivity parameters in the computational model remained significant after excluding outliers. We defined outliers as participants with a PGSI more than two standard deviations from the group mean; there were three such participants in the sample. As detailed in Table S4 below, all correlations remained significant when these participants were excluded from analysis.

Table S4. Spearman correlations excluding outliers ($N = 91$)

	w_{win}	w_{loss}	$w_{nearwin}$	$w_{nearloss}$	$w_{neutral}$	w_0	γ	ϕ
PGSI score	.35**	-.33**	-.34**	-.27**	-.31**	-.01	-.12	-.37**

** $p < .01$, uncorrected

Of the parameter correlations not discussed in the main text, the significant negative correlation between PGSI scores and the emotion precision parameter ϕ indicates that higher PGSI scores were associated with more residual variance in emotion self-reports. The non-significant PGSI correlations with w_0 and γ respectively indicate that PGSI scores were not associated with participants' average emotional valence or with individual differences in the 'decay rate' of the effects of slot machine outcomes on emotion.

We also conducted several additional linear regression analyses to confirm that emotional reactivity model parameters were still associated with (log-transformed) PGSI scores after controlling for age and gender. The results of these analyses, which are reported in Table S5a to S5e below, indicated that this was indeed the case.

Table S5a. Linear regression of $\log(\text{PGSI} + 1)$ for w_{win} model parameter

Coefficient	Sum of Squares	df	F	p	
Intercept	0.08	1	0.15	.70	
w_{win}	12.51	1	22.02	< .001	***
Age	1.37	1	2.41	.12	
Gender	4.36	3	2.56	.06	

Note: * $p < .05$; *** $p < .001$; residual $df = 88$

Table S5b. Linear regression of log(PGSI + 1) for w_{loss} model parameter

Coefficient	Sum of Squares	df	F	p	
Intercept	0	1	0.001	.98	
w_{loss}	10.63	1	18.02	< .001	***
Age	1.16	1	1.96	.16	
Gender	4.70	3	2.66	.05	

Note: * $p < .05$; *** $p < .001$; residual $df = 88$

Table S5c. Linear regression of log(PGSI + 1) for $w_{neutral}$ model parameter

Coefficient	Sum of Squares	df	F	p	
Intercept	0.90	1	1.50	.22	
$w_{neutral}$	9.72	1	16.21	< .001	***
Age	0.47	1	0.77	.38	
Gender	4.90	3	2.72	.049	*

Note: * $p < .05$; *** $p < .001$; residual $df = 88$

Table S5d. Linear regression of log(PGSI + 1) for $w_{nearwin}$ model parameter

Coefficient	Sum of Squares	df	F	p	
Intercept	0.39	1	0.66	.42	
$w_{nearwin}$	10.77	1	18.32	< .001	***
Age	0.71	1	1.21	.27	
Gender	4.90	3	2.78	.046	*

Note: * $p < .05$; *** $p < .001$; residual $df = 88$

Table S5e. Linear regression of log(PGSI + 1) for $w_{nearloss}$ model parameter

Coefficient	Sum of Squares	df	F	p	
Intercept	1.31	1	2.14	.15	
$w_{nearloss}$	8.68	1	14.18	< .001	***
Age	0.35	1	0.57	.45	
Gender	4.87	3	2.65	.05	

Note: * $p < .05$; *** $p < .001$; residual $df = 88$