Supplementary Table S1. Demographic and clinical characteristics.

	Clinical Study				Non-Clinical Study	
	AN	AN-WR	HC-L	HC-H	S0+S1	S2
	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)
N	31	23	38	35	170	315
Age	24.9 (8.72)	26.13 (7.5)	22.89 (3.29)	22.46 (4.67)	32.28 (10.58)	23.92 (6.63)
BMI	15.88 (1.48)	19.7 (1.72)	19.51 (0.91)	19.73 (0.83)	22.23 (2.61)	22.21 (4.33)
Illness duration (years)	7.55(8.17)	4.66(4.53)	-	-	-	-
Avg Pumps	25.73 (12.62)	24.66 (15.35)	33.41 (9.47)	31.58 (7.67)	34.35 (14.56)	33.15 (10.99)
Hesitance	589.09 (246.08)	580.36 (220.66)	300.7 (301.69)	357.28 (422.54)	-	303.26 (322.48)
EDE-Q Total	2.98 (1.67)	2.19 (1.75)	0.44 (0.51)	2.53 (1.07)	1.53 (1.12)	1.61 (1.26)
EDE-Q Restraint	2.44 (1.89)	1.91 (1.8)	0 (0)	2.83 (1.15)	1.46 (1.47)	1.31 (1.42)
DASS-21 Anxiety	7.5 (4.52)	6.27 (4.98)	5.56 (5.61)	5.5 (4.83)	-	5.77 (4.46)
DASS-21 Depression	12.65 (5.94)	7.91 (6.02)	4.56 (4.19)	6.5 (4.65)	-	4.81 (4.09)
DASS-21 Stress	13.04 (4.89)	8.82 (5.32)	6.22 (5.02)	8.21 (4.28)	-	7.74 (4.53)
OCD-10 Total	-	-	12.67 (8.47)	23.86 (14.35)	-	21.09 (13.25)
BIS-11 Total	-	-	64.92 (11.99)	69.45 (11.32)	-	68.13 (11.42)
Psychiatric Comorbidities	14 Mood disorder	9 Mood disorder				
	5 GAD	6 GAD				
	9 OCD	4 OCD				
	3 Panic disorder	6 Panic disorder				
	2 Personality disorder	0 Personality disorder				
Current Medication	4 Antidepressants	1 Antidepressants				
	2 Sedatives	0 Sedatives				
	1 Anxiolytics	1 Anxiolytics				
	3 Antipsychotics	1 Antipsychotics				

Note: one AN participant was removed from the Hesitance overall mean because she was an outlier in overall slowness. Anxiety disorders includes panic disorder; mood disorders include MDD. Dashes indicate measure not taken.

Supplementary Table S2. Results of uncertainty vs. risk computational modelling analyses in non-clinical (upper half) and clinical (lower half) samples

	non-Clinical Prior Probability of Loss Belief (exploration)				non-Clinical Prior Hesitance (exploration)			
Effect	**β(sd)**	**p**	X^2**(df)**	f^2	**β(sd)**	**p**	X^2**(df)**	f^2
EDE-Q Restraint	0.02(0.02)	0.325	0.97(1)	0.02	1.24(9.14)	0.892	0.02(1)	0.044
Stimulus x Direction x EDE-Q Restraint	0.01(0.04)	0.442	2.69(3)	0.021	9.41(17.27)	0.825	0.9(3)	0.055

	non-Clinical Posterior Probability of Loss Belief (exploitation)				non-Clinical Posterior Hesitance (exploitation)			
Effect	**β(sd)**	**p**	X^2**(df)**	f^2	**β(sd)**	**p**	X^2**(df)**	f^2
EDE-Q Restraint	0.04(0.02)	**0.018**	5.57(1)	0.014	-1.99(8.48)	0.814	0.06(1)	0.050
Stimulus x Direction x EDE-Q Restraint	-0.01(0.03)	0.379	3.08(3)	0.014	11.75(13.82)	0.773	1.12(3)	0.068

	Clinical Prior Probability of Loss Belief (exploration)				Clinical Prior Hesitance (exploration)			
Effect	**β(sd)**	**p**	X^2**(df)**	f^2	**β(sd)**	**p**	X^2**(df)**	f^2
GROUP		**0.043**	8.15(3)	0.048		**<0.001**	19.63(3)	0.121
AN vs HC_L	0.29(0.15)	0.065	3.4(1)	0.038	307.32(65.85)	**<0.001**	18.72(1)	0.216
AN-WR vs HC_L	0.34(0.15)	**0.029**	4.79(1)	0.076	313.04(71.74)	**<0.001**	16.63(1)	0.172
HC_H vs HC_L	0.05(0.09)	0.598	0.28(1)	0.026	68.93(81.48)	0.399	0.71(1)	0.023
Stimulus x Direction x GROUP		0.284	10.88(9)	0.075		0.162	13(9)	0.135

	Clinical Posterior Probability of Loss Belief (exploitation)				Clinical Posterior Hesitance (exploitation)			
Effect	**β(sd)**	**p**	X^2**(df)**	f^2	**β(sd)**	**p**	X^2**(df)**	f^2
GROUP		**0.002**	14.96(3)	0.105		**<0.001**	18.98(3)	0.145
AN vs HC_L	0.39(0.16)	**0.019**	5.46(1)	0.071	310.53(67.94)	**<0.001**	18.15(1)	0.242
AN-WR vs HC_L	0.53(0.18)	**0.004**	8.07(1)	0.127	254.11(75.08)	**0.001**	10.49(1)	0.146
HC_H vs HC_L	0.01(0.1)	0.958	0(1)	0.052	49.37(81.65)	0.546	0.36(1)	0.017
Stimulus x Direction x GROUP		0.527	8.07(9)	0.116		0.297	10.69(9)	0.149

Supplementary Materials 1 - Non-Clinical

Contents

S0 and S1 Study EDE-Q Restraint Slopes

This table shows the results of 6 Linear Regressions (nbClicks~AGE+BMI+EDE_Q_Restraint), one per condition for Study 0, Study 1 and the merge of Study 0 + Study 1. * *p<0.05*, ** *p<0.01* and *** *p<0.001*. BODE stands for *Body Decrease* and BOIN for *Body Increase*.

Variable	S0 BOIN	S0 BODE	S1 BOIN	S1 BODE	S0&S1 BOIN	S0&S1 BODE
Stimulus	Body	Body	Body	Body	Body	Body
Direction	Increase	Decrease	Increase	Decrease	Increase	Decrease
N	23	12	67	68	90	80
Intercept	36.53	34.05	39.03*	39.63**	33.48*	37.43**
AGE Slope	-0.28	0.51	0.08	-0.18	-0.1	-0.05
BMI Slope	0.27	-0.97	-0.17	0.2	0.26	0.04
EDE-Q Restraint Slope	**-3.34**	**-2.65**	**-1.44**	**-0.86**	**-1.66**	**-1.09**

In all cases (Study 0, Study 1 and Study 0 + Study 1) the slope of the *Body Increase* is more negative than the slope of *Body Decrease*. This indicates that, in line with our hypothesis, as EDE-Q Restraint increases, participants take less risk in *Body Increase* relative to *Body Decrease* conditions. The results are not statistically significant, but the effect size of the comparison is proportionally high comparing to the slopes (e.g. for Study 0 + Study 1 we have (BODE-BOIN)/BOIN= -34.3 %), which indicated that with a larger sample and a within-participants design, we would be able to measure the relevant interactions with greater statistical power.

Main Results Step-wise Analysis

The following sequential steps took place in this process: a) we used the Random Effects as the baseline model, b) we evaluated the effect of Age and BMI with respect to the baseline, c) we evaluated the effects of Stimulus and Direction independently as well as their interaction with respect to the previous steps, d) we evaluated the effect of EDE-Q Restraint and its interaction with Stimulus and Direction with respect to the previous steps (i.e. the three-way interaction between EDE-Q x Stimulus x Direction). Where this three-way interaction was the winning model (i.e. the model providing a significantly better fit for the data than any of the simpler models, as determined by our hierarchical MLM procedure) we subsequently broke down this interaction by performed a similar step-wise Multilevel analysis to evaluate the significance and effect of two planned comparisons/interactions of interest. We were specifically interested in establishing if individuals with higher levels of eating restraint took less risk when reward was coupled with an ‘undesirable’ body outcome (i.e. increasing size), while taking more risk when the outcome was a ‘desirable’ body (i.e. decreasing size). We therefore compared the regression slopes of each body condition with its respective balloon control condition (i.e. body increase vs. balloon increase; and body decrease vs. balloon decrease).

Clicks vs Stimulus*Direction*EDE-Q Restraint (S0+S1+S2)

Models Description

Random Effects

PARTICIPANT ID (SUBJ_ID), ORDER (OrderF), EXPERIMENTER

Fixed Effects

Model	IV
lm1	
lm2	AGE
lm3	AGE + BMI
lm4	AGE + BMI + Stimulus
lm5	AGE + BMI + Stimulus + Direction
lm6	AGE + BMI + Stimulus x Direction
lm7	AGE + BMI + Stimulus x Direction+EDE_Q_Restraint
lm8	AGE + BMI + Stimulus x Direction x EDE_Q_Restraint

Step-wise Comparison Results

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
lm1	5	150536.1	150575.4	-75263.04	150526.1	NA	NA	NA
lm2	6	150531.1	150578.2	-75259.53	150519.1	7.013	1	0.008
lm3	7	150532.5	150587.5	-75259.26	150518.5	0.545	1	0.461
lm4	8	150531.1	150594.0	-75257.55	150515.1	3.416	1	0.065
lm5	9	150530.2	150600.9	-75256.11	150512.2	2.885	1	0.089
lm6	10	150531.4	150610.0	-75255.70	150511.4	0.824	1	0.364
lm7	11	150528.9	150615.3	-75253.46	150506.9	4.480	1	0.034
lm8	14	150516.1	150626.1	-75244.06	150488.1	18.794	3	0.000

Final Model Coefficients

	Estimate	Std. Error	t value
(Intercept)	36.51	3.83	9.54
AGE	-0.19	0.07	-2.83
BMI	0.14	0.14	0.95
StimulusBody	-0.54	0.35	-1.52
DirectionIncrease	-0.55	0.36	-1.55
EDE_Q_Restraint	-0.58	0.40	-1.44
StimulusBody:DirectionIncrease	1.25	0.50	2.50
StimulusBody:EDE_Q_Restraint	0.02	0.19	0.11
DirectionIncrease:EDE_Q_Restraint	0.05	0.19	0.29
StimulusBody:DirectionIncrease:EDE_Q_Restraint	-0.70	0.26	-2.67

Inter-correlation Coefficients (final model)

Random Effect (Level)	ICC %
SUBJ_ID	46.86
STUDY	2.76

OrderF	0.51
Residual	49.87

Hesitance vs Stimulus*Direction*EDE-Q Restraint (S0+S1+S2)

Models Description

Random Effects

Same as for "Clicks".

Fixed Effects

Same as for "Clicks".

Step-wise Comparison Results

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
lm1	5	261933.2	261972.3	-130961.6	261923.2	NA	NA	NA
lm2	6	261917.1	261964.0	-130952.5	261905.1	18.119	1	0.000
lm3	7	261918.4	261973.2	-130952.2	261904.4	0.633	1	0.426
lm4	8	261862.8	261925.3	-130923.4	261846.8	57.620	1	0.000
lm5	9	261861.9	261932.3	-130922.0	261843.9	2.887	1	0.089
lm6	10	261862.1	261940.3	-130921.1	261842.1	1.804	1	0.179
lm7	11	261864.0	261950.0	-130921.0	261842.0	0.146	1	0.703
lm8	14	261859.4	261968.8	-130915.7	261831.4	10.567	3	0.014

Final Model Coefficients

	Estimate	Std. Error	t value
(Intercept)	152.46	121.86	1.25
AGE	6.02	1.41	4.26
BMI	-1.96	2.73	-0.72
StimulusBody	34.69	8.71	3.98
DirectionIncrease	-0.42	8.78	-0.05
EDE_Q_Restraint	-8.48	8.18	-1.04
StimulusBody:DirectionIncrease	-23.51	12.36	-1.90
StimulusBody:EDE_Q_Restraint	4.60	4.58	1.00
DirectionIncrease:EDE_Q_Restraint	-0.83	4.62	-0.18
StimulusBody:DirectionIncrease:EDE_Q_Restraint	8.67	6.49	1.34

Inter-correlation Coefficients (final model)

Random Effect (Level)	ICC %
SUBJ_ID	26.92

OrderF	5.92
STUDY	17.20
Residual	49.96

“Uncertainty” Model (Exploration & Exploitation) ~ Stimulus*Direction*EDE-Q Restraint (S0+S1+S2)

dv	iv	N	obs	reporting_result
log(pBurst_1)	EDE_Q_Restraint	481	1416	b=0.02(0.02), t=0.98, X^2(1)=0.97, p= 0.325, R^2=0.019, f^2=0.02
log(pBurst_1)	Stimulus x Direction x EDE_Q_Restraint	481	1416	b=0.01(0.04), t=0.21, X^2(3)=2.69, p= 0.442, R^2=0.021, f^2=0.021
log(pBurst_2)	EDE_Q_Restraint	481	1416	b=0.04(0.02), t=2.36, X^2(1)=5.57, p= 0.018, R^2=0.013, f^2=0.014
log(pBurst_2)	Stimulus x Direction x EDE_Q_Restraint	481	1416	b=-0.01(0.03), t=-0.31, X^2(3)=3.08, p= 0.379, R^2=0.013, f^2=0.014
threshold	EDE_Q_Restraint	481	1416	b=-0.05(0.11), t=-0.51, X^2(1)=0.26, p= 0.608, R^2=0.01, f^2=0.011
threshold	Stimulus x Direction x EDE_Q_Restraint	481	1416	b=-0.95(0.4), t=-2.38, X^2(3)=7.69, p= 0.053, R^2=0.017, f^2=0.017
avgPumps_1	EDE_Q_Restraint	481	1416	b=-0.36(0.21), t=-1.68, X^2(1)=2.82, p= 0.093, R^2=0.018, f^2=0.018
avgPumps_1	Stimulus x Direction x EDE_Q_Restraint	481	1416	b=-0.51(0.62), t=-0.83, X^2(3)=2.49, p= 0.477, R^2=0.019, f^2=0.02
avgPumps_2	EDE_Q_Restraint	481	1416	b=-0.28(0.24), t=-1.17, X^2(1)=1.37, p= 0.242, R^2=0.007, f^2=0.007
avgPumps_2	Stimulus x Direction x EDE_Q_Restraint	481	1416	b=-0.45(0.56), t=-0.8, X^2(3)=1.09, p= 0.779, R^2=0.007, f^2=0.007
1000*log(avgLastTime_1)	EDE_Q_Restraint	446	1378	b=1.24(9.14), t=0.14, X^2(1)=0.02, p= 0.892, R^2=0.042, f^2=0.044
1000*log(avgLastTime_1)	Stimulus x Direction x EDE_Q_Restraint	446	1378	b=9.41(17.27), t=0.55, X^2(3)=0.9, p= 0.825, R^2=0.052, f^2=0.055
1000*log(avgLastTime_2)	EDE_Q_Restraint	445	1379	b=-1.99(8.48), t=-0.24, X^2(1)=0.06, p= 0.814, R^2=0.047, f^2=0.05
1000*log(avgLastTime_2)	Stimulus x Direction x EDE_Q_Restraint	445	1379	b=11.75(13.82), t=0.85, X^2(3)=1.12, p= 0.773, R^2=0.063, f^2=0.068

“Risk” Model (Exponential Weight Model) ~ Stimulus*Direction*EDE-Q Restraint (S2)

dv	iv	N	obs	reporting_result
m_EU_phi_mean_L	EDE_Q_Restraint	312	1247	b=0.08(0.04), t=1.99, X^2(1)=3.92, **p= 0.048**, R^2=0.037, f^2=0.038

m_EU_phi_mean_L	Stimulus x Direction x EDE_Q_Restraint	312	1247	b=0(0.03), t=-0.13, X^2(3)=3.62, p= 0.305, R^2=0.037, f^2=0.039
m_EU_rho_mean	EDE_Q_Restraint	312	1247	b=-0.02(0.01), t=-3.39, X^2(1)=11.22, **p<0.001**, R^2=0.063, f^2=0.067
m_EU_rho_mean	Stimulus x Direction x EDE_Q_Restraint	312	1247	b=0(0), t=-0.57, X^2(3)=4.11, p= 0.25, R^2=0.063, f^2=0.068
log(m_EU_lambda_mean)	EDE_Q_Restraint	312	1247	b=0.01(0.03), t=0.42, X^2(1)=0.18, p= 0.675, R^2=0.001, f^2=0.001
log(m_EU_lambda_mean)	Stimulus x Direction x EDE_Q_Restraint	312	1247	b=0.01(0.01), t=1.03, X^2(3)=1.47, p= 0.689, R^2=0.001, f^2=0.001
m_EU_tau_mean	EDE_Q_Restraint	312	1247	b=-18.85(22.26), t=-0.85, X^2(1)=0.72, p= 0.398, R^2=0.003, f^2=0.003
m_EU_tau_mean	Stimulus x Direction x EDE_Q_Restraint	312	1247	b=-13.08(44.16), t=-0.3, X^2(3)=0.19, p= 0.979, R^2=0.004, f^2=0.004
m_EU_eta_mean	EDE_Q_Restraint	312	1247	b=0(0), t=0.87, X^2(1)=0.75, p= 0.387, R^2=0.011, f^2=0.011
m_EU_eta_mean	Stimulus x Direction x EDE_Q_Restraint	312	1247	b=0(0), t=0.9, X^2(3)=3.33, p= 0.344, R^2=0.011, f^2=0.011

Model Validation

Model Validation Exploration vs Exploitation: Average Collected Clicks, Coefficient of Variation, Hesitance (S2)

Both Hesitance and the Coefficient of Variation are significantly higher in Exploration than in Exploitation. On the contrary, the Average Collected Clicks are higher in Exploitation.

	avgPumps_2 - avgPumps_1			**z2 - z1**			**log(avgLastTime_2) - log(avgLastTime_1)**			**pBurst_2_L - pBurst_1_L**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	1.38	0.41 – 2.35	**0.005**	-0.10	-0.13 – -0.06	**<0.001**	-0.07	-0.14 – -0.01	**0.024**	0.07	-0.02 – 0.16	0.153
Random Effects												
σ^2	92.36			0.23			0.05			0.33		
τ_{00}	5.02 SUBJ_ID			0.01 SUBJ_ID			0.00 SUBJ_ID			0.03 SUBJ_ID		
	0.62 OrderF			0.00 OrderF			0.00 OrderF			0.01 OrderF		
ICC	0.06			0.03			0.08			0.10		
N	4 OrderF			4 OrderF			4 OrderF			4 OrderF		
	312 SUBJ_ID			312 SUBJ_ID			312 SUBJ_ID			312 SUBJ_ID		
Observations	1247			1246			1246			1247		
Marginal R^2 / Conditional R^2	0.000 / 0.058			0.000 / 0.029			0.000 / 0.075			0.000 / 0.103		

Control Variable Analysis

Correlations: EDE-Q vs Control Variables

	avgClicks	avgLastTrialTime	EDE_Q_Restraint	EDE_Q_Total	BIDQ_TOTAL	Dass21_Depression	Dass21_Anxiety	Dass21_Stress	BIS11_Total	OCIR_TOTAL
avgClicks	1.00	0.13	-0.11	-0.11	-0.05	-0.10	0.05	0.00	-0.03	-0.11
avgLastTrialTime	0.13	1.00	-0.06	-0.13	0.00	-0.03	-0.04	-0.09	-0.34	-0.06
EDE_Q_Restraint	-0.11	-0.06	1.00	0.81	0.36	0.17	0.02	0.23	0.12	0.33
EDE_Q_Total	-0.11	-0.13	0.81	1.00	0.58	0.36	0.23	0.36	0.17	0.45
BIDQ_TOTAL	-0.05	0.00	0.36	0.58	1.00	0.36	0.37	0.39	-0.04	0.51
Dass21_Depression	-0.10	-0.03	0.17	0.36	0.36	1.00	0.57	0.60	-0.01	0.44
Dass21_Anxiety	0.05	-0.04	0.02	0.23	0.37	0.57	1.00	0.58	-0.01	0.52
Dass21_Stress	0.00	-0.09	0.23	0.36	0.39	0.60	0.58	1.00	-0.01	0.49
BIS11_Total	-0.03	-0.34	0.12	0.17	-0.04	-0.01	-0.01	-0.01	1.00	0.04
OCIR_TOTAL	-0.11	-0.06	0.33	0.45	0.51	0.44	0.52	0.49	0.04	1.00

DASS-21, BIS-11, OCIR, BIDQ covariates for Risk-taking

To examine the possible effect of covariates in our Risk-taking main findings, we used the same step-wise Multi-level Modelling analysis with final-step models:
nbClicks~XXX+AGE+BMI+EDE_Q_Restraint+(1|SUBJ_ID)+(1|Order)+(1|Experimenter)
nbClicks~XXX+AGE+BMI+Stimulus*Direction*EDE_Q_Restraint+(1|SUBJ_ID)+(1|Order)+(1|Experimenter)
where XXX was the relevant Covariate.

Covariate	iv	N	obs	reporting_result
BIDQ_TOTAL	EDE_Q_Restraint	115	6399	b=-0.79(0.79), t=-1, $X^2(1)$=0.99, p=0.321, R^2=0.013, f^2=0.013
BIDQ_TOTAL	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=-1.3(0.4), t=-3.28, $X^2(3)$=31.64, **p<0.001**, R^2=0.016, f^2=0.016
DASS Depression	EDE_Q_Restraint	115	6399	b=-0.78(0.76), t=-1.03, $X^2(1)$=1.07, p=0.302, R^2=0.013, f^2=0.013
DASS Depression	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=-1.3(0.4), t=-3.28, $X^2(3)$=31.64, **p<0.001**, R^2=0.016, f^2=0.016

DASS Anxiety	EDE_Q_Restraint	115	6399	b=-0.79(0.74), t=-1.07, $X^2(1)$=1.14, p= 0.286, R^2=0.014, f^2=0.014
DASS Anxiety	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=-1.3(0.4), t=-3.28, $X^2(3)$=31.62, **p<0.001**, R^2=0.017, f^2=0.018
DASS Stress	EDE_Q_Restraint	115	6399	b=-0.87(0.76), t=-1.15, $X^2(1)$=1.31, p= 0.253, R^2=0.014, f^2=0.014
DASS Stress	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=-1.3(0.4), t=-3.28, $X^2(3)$=31.63, **p<0.001**, R^2=0.017, f^2=0.018
OCIR	EDE_Q_Restraint	115	6399	b=-0.48(0.78), t=-0.62, $X^2(1)$=0.38, p= 0.537, R^2=0.018, f^2=0.019
OCIR	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=-1.3(0.4), t=-3.28, $X^2(3)$=31.65, **p<0.001**, R^2=0.022, f^2=0.022
BIS11_Total	EDE_Q_Restraint	275	14836	b=-0.71(0.46), t=-1.55, $X^2(1)$=2.4, p= 0.121, R^2=0.039, f^2=0.041
BIS11_Total	Stimulus x Direction x EDE_Q_Restraint	275	14836	b=-0.76(0.28), t=-2.73, $X^2(3)$=26.94, **p<0.001**, R^2=0.04, f^2=0.041

We notice that in all cases, the three-way interaction remains statistically significant.

DASS-21, BIS-11, OCIR, BIDQ covariates for Hesitance

To examine the possible effect of covariates in our main Hesitance findings, we used the same step-wise Multi-level Modelling analysis with final-step models:
hesitance~XXX+AGE+BMI+EDE_Q_Restraint+(1|SUBJ_ID)+(1|Order)+(1|Experimenter)
hesitance~XXX+AGE+BMI+Stimulus*Direction*EDE_Q_Restraint+(1|SUBJ_ID)+(1|Order)+(1|Experimenter)
where XXX was the relevant Covariate.

Covariate	iv	N	obs	reporting_result
BIDQ_TOTAL	EDE_Q_Restraint	115	6399	b=16.28(14.9), t=1.09, $X^2(1)$=1.19, p= 0.276, R^2=0.17, f^2=0.205
BIDQ_TOTAL	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=12.16(11.45), t=1.06, $X^2(3)$=11.34, **p= 0.01**, R^2=0.173, f^2=0.21
DASS Depression	EDE_Q_Restraint	115	6399	b=14.5(14.3), t=1.01, $X^2(1)$=1.02, p= 0.312, R^2=0.17, f^2=0.205
DASS Depression	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=12.14(11.45), t=1.06, $X^2(3)$=11.33, **p= 0.01**, R^2=0.173, f^2=0.21
DASS Anxiety	EDE_Q_Restraint	115	6399	b=11.81(14.03), t=0.84, $X^2(1)$=0.71, p= 0.401, R^2=0.169, f^2=0.204
DASS Anxiety	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=12.17(11.45), t=1.06, $X^2(3)$=11.34, **p= 0.01**, R^2=0.172, f^2=0.208
DASS Stress	EDE_Q_Restraint	115	6399	b=13.75(14.33), t=0.96, $X^2(1)$=0.92, p= 0.338, R^2=0.169, f^2=0.204
DASS Stress	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=12.17(11.45), t=1.06, $X^2(3)$=11.34, **p= 0.01**, R^2=0.173, f^2=0.209

OCIR	EDE_Q_Restraint	115	6399	b=17.38(14.82), t=1.17, $X^2(1)$=1.37, p= 0.242, R^2=0.171, f^2=0.206
OCIR	Stimulus x Direction x EDE_Q_Restraint	115	6399	b=12.16(11.45), t=1.06, $X^2(3)$=11.32, **p= 0.01**, R^2=0.174, f^2=0.211
BIS11_Total	EDE_Q_Restraint	275	14836	b=5.97(11.67), t=0.51, $X^2(1)$=0.26, p= 0.609, R^2=0.106, f^2=0.119
BIS11_Total	Stimulus x Direction x EDE_Q_Restraint	275	14836	b=10.32(7.16), t=1.44, $X^2(3)$=13.91, **p= 0.003**, R^2=0.109, f^2=0.122

We notice that in all cases, the three-way interaction remains statistically significant.

DASS-21, BIS-11, OCIR, BIDQ covariates for Probability of Burst during Exploration (Phase 1)

To examine the possible effect of covariates in our computational modelling of uncertainty versus risk findings, we used the same step-wise Multi-level Modelling analysis of exploration (phase 1) with final-step models including relevant covariates:

DataSubset	dv	iv	N	obs	p	Xsqr	Xdf	Fsqr	reportii	result
S0+S1+S2	log(pBurst_1)	EDE_Q_Restrain	481	1416	p= 0.325	0.97	1	0.02	$b_{}$=0.02(0.02),	$t_{}$=0.98, X^2(1)=0.97, p=
S2 BIDQ_TOTAL	log(pBurst_1)	EDE_Q_Restrain	115	459	p= 0.643	0.22	1	-0.091	$b_{}$=0.02(0.04),	$t_{}$=0.46, X^2(1)=0.22, p=
S2 DASS Depression	log(pBurst_1)	EDE_Q_Restrain	115	459	p= 0.431	0.62	1	-0.092	$b_{}$=0.03(0.04),	$t_{}$=0.79, X^2(1)=0.62, p=
S2 DASS Anxiety	log(pBurst_1)	EDE_Q_Restrain	115	459	p= 0.456	0.56	1	-0.092	$b_{}$=0.03(0.04),	$t_{}$=0.75, X^2(1)=0.56, p=
S2 DASS Stress	log(pBurst_1)	EDE_Q_Restrain	115	459	p= 0.422	0.64	1	-0.092	$b_{}$=0.03(0.04),	$t_{}$=0.8, X^2(1)=0.64, p= 0.
S2 OCIR	log(pBurst_1)	EDE_Q_Restrain	115	459	p= 0.842	0.04	1	-0.082	$b_{}$=0.01(0.04),	$t_{}$=0.2, X^2(1)=0.04, p= 0.
S2 BIS11_Total	log(pBurst_1)	EDE_Q_Restrain	275	1099	p= 0.258	1.28	1	0.044	$b_{}$=0.02(0.02),	$t_{}$=1.13, X^2(1)=1.28, p=

We note that in all cases the non-significant 3-way interaction remained non-significant and with a similar slope.

DASS-21, BIS-11, OCIR, BIDQ covariates for Probability of Burst during Exploitation (Phase 2)

To examine the possible effect of covariates in our computational modelling of uncertainty versus risk findings, we used the same step-wise Multi-level Modelling analysis of exploitation (phase 2) with final-step models including relevant covariates:

DataSubset	dv	iv	N	obs	p	Xsqr	Xdf	Fsqr	reportii	result
S0+S1+S2	log(pBurst_2)	EDE_Q_Restrain	481	1416	p= 0.018	5.57	1	0.014	$b_{}$=0.04(0.02),	$t_{}$=2.36, X^2(1)=5.57, p= 0.018, $
S2 BIDQ_TOTAL	log(pBurst_2)	EDE_Q_Restrain	115	459	p= 0.503	0.45	1	-0.063	$b_{}$=0.03(0.04),	$t_{}$=0.67, X^2(1)=0.45, p= 0.503, $
S2 DASS Depression	log(pBurst_2)	EDE_Q_Restrain	115	459	p= 0.369	0.81	1	-0.062	$b_{}$=0.03(0.04),	$t_{}$=0.9, X^2(1)=0.81, p= 0.369, $R
S2 DASS Anxiety	log(pBurst_2)	EDE_Q_Restrain	115	459	p= 0.411	0.68	1	-0.064	$b_{}$=0.03(0.04),	$t_{}$=0.82, X^2(1)=0.68, p= 0.411, $
S2 DASS Stress	log(pBurst_2)	EDE_Q_Restrain	115	459	p= 0.395	0.72	1	-0.063	$b_{}$=0.03(0.04),	$t_{}$=0.85, X^2(1)=0.72, p= 0.395, $
S2 OCIR	log(pBurst_2)	EDE_Q_Restrain	115	459	p= 0.663	0.19	1	-0.058	$b_{}$=0.02(0.04),	$t_{}$=0.44, X^2(1)=0.19, p= 0.663, $
S2 BIS11_Total	log(pBurst_2)	EDE_Q_Restrain	275	1099	p= 0.175	1.84	1	0.082	$b_{}$=0.03(0.02),	$t_{}$=1.36, X^2(1)=1.84, p= 0.175, $

We note that the main effect of EDE-Q restraint is no longer significant but the slope direction remains the same but is slightly smaller owing to the reduced N from missing data for the covariates.

EDE-Q

Correlations: EDE-Q subscales

	EDE_Q_Restraint	EDE_Q_Total	EDE_Q_Eating	EDE_Q_Weight	EDE_Q_Shape	BIDQ_TOTAL
EDE_Q_Restraint	1.00	0.81	0.57	0.63	0.62	0.36
EDE_Q_Total	0.81	1.00	0.83	0.93	0.93	0.58
EDE_Q_Eating	0.57	0.83	1.00	0.71	0.69	0.44
EDE_Q_Weight	0.63	0.93	0.71	1.00	0.89	0.58
EDE_Q_Shape	0.62	0.93	0.69	0.89	1.00	0.64
BIDQ_TOTAL	0.36	0.58	0.44	0.58	0.64	1.00

EDE-Q Cronbach Alpha

S0: 0.9

S1: 0.85

S2: 0.91

S0+S1+S2: 0.89

Sensitivity Analyses

36 people, all in S2, with BMI<18.5

Number of clicks:

DataSubset	dv	iv	N	obs	p	Xsqr	Xdf	Fsqr	reporti	result
S0+S1+S2	colPumps	EDE_Q_Restrain	482	19106	p= 0.034	4.48	1	0.008	$b_{}$=-0.81(0.38), $t_{}$=-2.12, X^2(1)=4.48, p= 0.034, R^2	
S0+S1+S2	colPumps	Stimulus x Direction x El	482	19106	**p<0.001	18.79	3	0.008	$b_{}$=-0.7(0.26), $t_{}$=-2.67, X^2(3)=18.79, **p<0.001**, $	
S0+S1+S2 bmi>=18	colPumps	EDE_Q_Restrain	446	17177	p= 0.024	5.09	1	0.009	$b_{}$=-0.9(0.4), $t_{}$=-2.26, X^2(1)=5.09, p= 0.024, R^2=(	
S0+S1+S2 bmi>=18	colPumps	Stimulus x Direction x El	446	17177	p= 0.02	9.84	3	0.009	$b_{}$=-0.6(0.28), $t_{}$=-2.13, X^2(3)=9.84, p= 0.02, R^2=(	

We note that for risk taking (number of clicks) with vs without low BMIs the slope for the significant overall effect of EDE-Q restraint becomes slightly steeper/bigger, while the slop for the significant 3-way interaction becomes slightly shallower/smaller. The p-values change slightly but do not change in terms of meeting significance at alpha = 0.05

Hesitance:

DataSubset	dv	iv	N	obs	p	Xsqr	Xdf	Fsqr	reporti	result
S0+S1+S2	1000*log(lastTrialTime)	EDE_Q_Restrain	447	18340	p= 0.696	0.15	1	0.026	$b_{}$=-2.95(7.55), $t_{}$=-0.39, $X^2	
S0+S1+S2	1000*log(lastTrialTime)	Stimulus x Direction x El	447	18340	p= 0.014	10.57	3	0.035	$b_{}$=8.67(6.49), $t_{}$=1.34, X^2(	
S0+S1+S2 bmi>=18	1000*log(lastTrialTime)	EDE_Q_Restrain	411	16414	p= 0.816	0.05	1	0.027	$b_{}$=-1.81(7.78), $t_{}$=-0.23, $X^2	
S0+S1+S2 bmi>=18	1000*log(lastTrialTime)	Stimulus x Direction x El	411	16414	p= 0.003	13.68	3	0.041	$b_{}$=16.61(6.86), $t_{}$=2.42, X^2	

We note that for hesitance with vs without low BMIs the slope for the overall non-significant effect of EDE-Q restraint becomes slightly shallower/smaller, while the slope for the significant 3-way interaction becomes slightly steeper/bigger. The p-values change slightly but do not change in terms of meeting significance at alpha = 0.05

Supplementary Materials 2 - Clinical

Contents

Main Results Multi-level Step-wise Analysis

Following the same procedure used to analyse the non-clinical data: a) we used the Random Effects as the baseline model, b) we evaluated the effect of Age with respect to the baseline, c) we evaluated the effects of Stimulus and Direction independently as well as their interaction with respect to the previous steps, d) we evaluated the effect of Group and its interaction with Stimulus and Direction with respect to the previous steps. Subsequently, we performed a step-wise Multilevel analysis to evaluate the significance and effect of the three-way interaction, using the same planned comparisons described above for the non-clinical data analysis. However, instead of looking at the differences between conditions dependent on EDE-Q restraint scores, we compared in each analysis the relative difference in the slopes of the clinical groups to that of the HC-L group.

Clicks ~ Stimulus*Direction*GROUP

Models Description

Random Effects

PARTICIPANT ID (SUBJ_ID), ORDER (OrderF)

Fixed Effects

Model	IV
lm1	
lm2	AGE
lm3	AGE + Stimulus
lm4	AGE + Stimulus + Direction
lm5	AGE + Stimulus x Direction
lm6	AGE + Stimulus x Direction + GROUP
lm7	AGE + Stimulus x Direction x GROUP

Step-wise Comparison Results

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
lm1	4	54175.03	54202.42	-27083.52	54167.03	NA	NA	NA
lm2	5	54176.16	54210.39	-27083.08	54166.16	0.872	1	0.350
lm3	6	54178.05	54219.13	-27083.02	54166.05	0.114	1	0.736
lm4	7	54161.52	54209.44	-27073.76	54147.52	18.530	1	0.000
lm5	8	54159.88	54214.66	-27071.94	54143.88	3.632	1	0.057
lm6	11	54153.18	54228.50	-27065.59	54131.18	12.702	3	0.005
lm7	20	54143.82	54280.75	-27051.91	54103.82	27.361	9	0.001

Final Model Coefficients

	Estimate	Std. Error	t value
(Intercept)	34.67	4.16	8.33

AGE	-0.03	0.16	-0.21
StimulusBody	-0.05	0.72	-0.07
DirectionIncrease	-1.68	0.72	-2.33
GROUPAN	-7.90	2.78	-2.84
GROUPAN_WR	-9.51	3.05	-3.12
GROUPHC_H	-1.68	2.66	-0.63
StimulusBody:DirectionIncrease	1.41	1.02	1.38
StimulusBody:GROUPAN	2.09	1.07	1.94
StimulusBody:GROUPAN_WR	2.00	1.15	1.74
StimulusBody:GROUPHC_H	-0.78	1.03	-0.76
DirectionIncrease:GROUPAN	0.70	1.08	0.65
DirectionIncrease:GROUPAN_WR	1.66	1.16	1.43
DirectionIncrease:GROUPHC_H	1.88	1.04	1.82
StimulusBody:DirectionIncrease:GROUPAN	-3.97	1.52	-2.60
StimulusBody:DirectionIncrease:GROUPAN_WR	-3.87	1.62	-2.38
StimulusBody:DirectionIncrease:GROUPHC_H	-2.80	1.47	-1.91

Inter-correlation Coefficients (final model)

Random Effect (Level)	ICC %
SUBJ_ID	47.56
OrderF	0.27
Residual	52.18

Planned Contrasts: Stimulus*GROUP

Direction	iv	N	obs	reporting_result
ANvsHC_L - Direction==Increase	Stimulus x GROUP	67	1837	b_{AN}=-1.93(1.01), t_{AN}=-1.9, $X^2(1)$=3.61, p= 0.058, R^2=0.078, f^2=0.085
ANvsHC_L - Direction==Decrease	Stimulus x GROUP	69	1874	b_{AN}=4.11(1.03), t_{AN}=3.99, $X^2(1)$=15.49, **p<0.001**, R^2=0.046, f^2=0.049
AN-WR vsHC_L - Direction==Increase	Stimulus x GROUP	61	1680	b_{RE}=-2.37(1.1), t_{RE}=-2.16, $X^2(1)$=4.66, p= **0.031**, R^2=0.065, f^2=0.069
AN-WR vsHC_L - Direction==Decrease	Stimulus x GROUP	61	1688	b_{RE}=2.65(1.11), t_{RE}=2.39, $X^2(1)$=5.68, p= **0.017**, R^2=0.056, f^2=0.06

Hesitance ~ Stimulus*Direction*GROUP

Models Description

Random Effects

Same as for “Clicks”.

Fixed Effects

Same as for “Clicks”.

Step-wise Comparison Results

	npar	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
lm1	4	99027.35	99054.73	-49509.67	99019.35	NA	NA	NA
lm2	5	99026.63	99060.86	-49508.32	99016.63	2.718	1	0.099
lm3	6	99005.18	99046.26	-49496.59	98993.18	23.447	1	0.000
lm4	7	99007.17	99055.09	-49496.58	98993.17	0.014	1	0.906
lm5	8	99006.95	99061.71	-49495.47	98990.95	2.223	1	0.136
lm6	11	98991.69	99066.99	-49484.84	98969.69	21.259	3	0.000
lm7	20	98967.85	99104.76	-49463.92	98927.85	41.842	9	0.000

Final Model Coefficients

	Estimate	Std. Error	t value
(Intercept)	152.10	124.26	1.22
AGE	3.45	4.43	0.78
StimulusBody	49.21	18.11	2.72
DirectionIncrease	36.98	18.17	2.04
GROUPAN	273.63	75.62	3.62
GROUPAN_WR	252.33	82.97	3.04
GROUPHC_H	52.52	72.52	0.72
StimulusBody:DirectionIncrease	-99.16	25.74	-3.85
StimulusBody:GROUPAN	20.15	27.07	0.74
StimulusBody:GROUPAN_WR	-0.31	29.00	-0.01
StimulusBody:GROUPHC_H	-35.81	26.04	-1.38
DirectionIncrease:GROUPAN	-22.78	27.17	-0.84
DirectionIncrease:GROUPAN_WR	-14.72	29.13	-0.51
DirectionIncrease:GROUPHC_H	-61.88	26.12	-2.37
StimulusBody:DirectionIncrease:GROUPAN	108.21	38.45	2.81
StimulusBody:DirectionIncrease:GROUPAN_WR	38.03	40.94	0.93
StimulusBody:DirectionIncrease:GROUPHC_H	164.41	37.01	4.44

Inter-correlation Coefficients (final model)

Random Effect (Level)	ICC %
SUBJ_ID	48.84
OrderF	5.74
Residual	45.42

Planned Contrasts: Stimulus*GROUP

Direction	iv	N	obs	reporting_result
ANvsHC_L - Direction==Increase	Stimulus x GROUP	67	1836	b_{AN}=124.95(27.66), t_{AN}=4.52, $X^2(1)$=20.27, **p<0.001**, R^2=0.168, f^2=0.202
ANvsHC_L - Direction==Decrease	Stimulus x GROUP	69	1874	b_{AN}=12.87(26.64), t_{AN}=0.48, $X^2(1)$=0.23, p= 0.63, R^2=0.124, f^2=0.142
AN-WR vsHC_L - Direction==Increase	Stimulus x GROUP	61	1679	b_{RE}=35.73(27.59), t_{RE}=1.3, $X^2(1)$=1.68, p= 0.195, R^2=0.108, f^2=0.121
AN-WR vsHC_L - Direction==Decrease	Stimulus x GROUP	61	1687	b_{RE}=19.66(28.01), t_{RE}=0.7, $X^2(1)$=0.49, p= 0.483, R^2=0.108, f^2=0.121

Modelling “Uncertainty” (Exploration & Exploitation) Probability of Loss, Hesitance, Risk-Taking and Threshold ~ Stimulus*Direction*GROUP

dv	iv	N	obs	reporting_result
log(pBurst_1)	GROUP	127	502	b_{AN}=0.28(0.14), t_{AN}=1.97, b_{RE}=0.38(0.16), t_{RE}=2.42, b_{HC_H}=0.04(0.14), t_{HC_H}=0.3, $X^2(3)$=8.15, p= 0.043, R^2=0.045, f^2=0.048
log(pBurst_1)	Stimulus x Direction x GROUP	127	502	b_{AN}=0.5(0.25), t_{AN}=2.01, b_{RE}=0.51(0.26), t_{RE}=1.92, b_{HC_H}=0.41(0.23), t_{HC_H}=1.76, $X^2(9)$=10.88, p= 0.284, R^2=0.07, f^2=0.075
log(pBurst_2)	GROUP	127	502	b_{AN}=0.39(0.15), t_{AN}=2.52, b_{RE}=0.54(0.17), t_{RE}=3.16, b_{HC_H}=-0.01(0.15), t_{HC_H}=-0.04, $X^2(3)$=14.96, p= 0.002, R^2=0.095, f^2=0.105
log(pBurst_2)	Stimulus x Direction x GROUP	127	502	b_{AN}=0.47(0.21), t_{AN}=2.22, b_{RE}=0.31(0.23), t_{RE}=1.38, b_{HC_H}=0.06(0.2), t_{HC_H}=0.32, $X^2(9)$=8.07, p= 0.527, R^2=0.104, f^2=0.116
threshold	GROUP	127	502	b_{AN}=-0.82(0.81), t_{AN}=-1.01, b_{RE}=-1.92(0.88), t_{RE}=-2.18, b_{HC_H}=-0.9(0.77), t_{HC_H}=-1.17, $X^2(3)$=4.75, p= 0.191, R^2=0.018, f^2=0.018
threshold	Stimulus x Direction x GROUP	127	502	b_{AN}=2.86(2.86), t_{AN}=1, b_{RE}=-1.27(3.08), t_{RE}=-0.41, b_{HC_H}=4.5(2.73), t_{HC_H}=1.65, $X^2(9)$=13.59, p= 0.138, R^2=0.051, f^2=0.053
avgPumps_1	GROUP	127	502	b_{AN}=-4.08(1.44), t_{AN}=-2.83, b_{RE}=-4.11(1.58), t_{RE}=-2.61, b_{HC_H}=-1.38(1.38), t_{HC_H}=-1.01, $X^2(3)$=10.59, p= 0.014, R^2=0.036, f^2=0.037
avgPumps_1	Stimulus x Direction x GROUP	127	502	b_{AN}=4.96(3.96), t_{AN}=1.25, b_{RE}=3.97(4.26), t_{RE}=0.93, b_{HC_H}=0.38(3.78), t_{HC_H}=0.1, $X^2(9)$=5.87, p= 0.753, R^2=0.045, f^2=0.047
avgPumps_2	GROUP	127	502	b_{AN}=-5.49(1.52), t_{AN}=-3.6, b_{RE}=-5.17(1.67), t_{RE}=-3.1, b_{HC_H}=0.25(1.46), t_{HC_H}=0.17, $X^2(3)$=21.02, **p<0.001**, R^2=0.095, f^2=0.105

avgPumps_2	Stimulus x Direction x GROUP	127	502	b_{AN}=-1.93(3.33), t_{AN}=-0.58, b_{RE}=-2.2(3.58), t_{RE}=-0.61, b_{HC_H}=0.35(3.18), t_{HC_H}=0.11, X^2(9)=11.3, p= 0.256, R^2=0.113, f^2=0.128
1000*log(avgLastTime_1)	GROUP	126	500	b_{AN}=285.5(76.94), t_{AN}=3.71, b_{RE}=300.74(83.89), t_{RE}=3.58, b_{HC_H}=63.95(73.23), t_{HC_H}=0.87, X^2(3)=19.63, **p<0.001**, R^2=0.108, f^2=0.121
1000*log(avgLastTime_1)	Stimulus x Direction x GROUP	126	500	b_{AN}=143.42(110.23), t_{AN}=1.3, b_{RE}=23.81(117.56), t_{RE}=0.2, b_{HC_H}=172.2(104.57), t_{HC_H}=1.65, X^2(9)=13, p= 0.162, R^2=0.119, f^2=0.135
1000*log(avgLastTime_2)	GROUP	126	500	b_{AN}=291.14(74.35), t_{AN}=3.92, b_{RE}=240.76(81.12), t_{RE}=2.97, b_{HC_H}=45.5(70.83), t_{HC_H}=0.64, X^2(3)=18.98, **p<0.001**, R^2=0.126, f^2=0.145
1000*log(avgLastTime_2)	Stimulus x Direction x GROUP	126	500	b_{AN}=79.69(79.46), t_{AN}=1, b_{RE}=46.02(84.76), t_{RE}=0.54, b_{HC_H}=151.87(75.39), t_{HC_H}=2.01, X^2(9)=10.69, p= 0.297, R^2=0.129, f^2=0.149

Modelling "Exponential Weight" parameters ~ Stimulus*Direction*GROUP

dv	iv	N	obs	reporting_result
m_EU_phi_mean_L	GROUP	127	503	b_AN=0.37(0.28), t_AN=1.32, b_RE=0.25(0.31), t_RE=0.8, b_HC_H=0.27(0.27), t_HC_H=1.02, X^2(3)=1.97, p= 0.579, R^2=0.017, f^2=0.017
m_EU_phi_mean_L	Stimulus x Direction x GROUP	127	503	b_AN=-0.21(0.17), t_AN=-1.26, b_RE=0.12(0.18), t_RE=0.66, b_HC_H=-0.12(0.16), t_HC_H=-0.74, X^2(9)=6.05, p= 0.735, R^2=0.019, f^2=0.019
m_EU_rho_mean	GROUP	127	503	b_AN=-0.1(0.05), t_AN=-2.08, b_RE=-0.09(0.05), t_RE=-1.75, b_HC_H=-0.05(0.04), t_HC_H=-1.08, X^2(3)=5.17, p= 0.16, R^2=0.063, f^2=0.067
m_EU_rho_mean	Stimulus x Direction x GROUP	127	503	b_AN=0.03(0.02), t_AN=1.57, b_RE=0.06(0.02), t_RE=3.17, b_HC_H=0.04(0.02), t_HC_H=2.78, X^2(9)=23, **p= 0.006**, R^2=0.064, f^2=0.068
log(m_EU_lambda_mean)	GROUP	127	503	b_AN=0(0.17), t_AN=-0.02, b_RE=0.27(0.18), t_RE=1.49, b_HC_H=0.01(0.16), t_HC_H=0.09, X^2(3)=2.82, p= 0.42, R^2=0.022, f^2=0.023
log(m_EU_lambda_mean)	Stimulus x Direction x GROUP	127	503	b_AN=0.04(0.06), t_AN=0.59, b_RE=0.14(0.07), t_RE=2.13, b_HC_H=0.07(0.06), t_HC_H=1.21,

				X^2(9)=13.97, p= 0.123, R^2=0.023, f^2=0.024
m_EU_tau_mean	GROUP	127	503	b_AN=14.83(28.48), t_AN=0.52, b_RE=-3.94(31.23), t_RE=-0.13, b_HC_H=-13.68(27.26), t_HC_H=-0.5, X^2(3)=0.98, p= 0.806, R^2=0.009, f^2=0.009
m_EU_tau_mean	Stimulus x Direction x GROUP	127	503	b_AN=-48.21(66.28), t_AN=-0.73, b_RE=74.38(71.48), t_RE=1.04, b_HC_H=-41.58(63.39), t_HC_H=-0.66, X^2(9)=11.65, p= 0.234, R^2=0.029, f^2=0.029
m_EU_eta_mean	GROUP	127	503	b_AN=0.03(0.03), t_AN=1.22, b_RE=0.06(0.03), t_RE=2.01, b_HC_H=0.03(0.02), t_HC_H=1.14, X^2(3)=4.18, p= 0.243, R^2=0.033, f^2=0.034
m_EU_eta_mean	Stimulus x Direction x GROUP	127	503	b_AN=0(0), t_AN=-1.25, b_RE=0(0), t_RE=-0.82, b_HC_H=0(0), t_HC_H=0.65, X^2(9)=17.69, **p= 0.039**, R^2=0.033, f^2=0.034

HC-L and HC-H group description/selection

Two control groups were constructed from the non-clinical participants from Study 2. To account for the effect of BMI within the healthy controls, we first matched their BMI with that of the *AN-WR* group (which was achieved by selecting the participants with BMI less than the median of our sample), and then by splitting the remaining participants into group *HC-L* (Healthy Controls Low) who had EDE-Q Restraint in the lowest quartile, and group *HC-H* (Healthy Controls High) who had EDE-Q Restraint in the highest quartile of our sample. We thus ended up with N=38 participants in the *HC-L* group and N=35 participants in the *HC-H* group.

Control Variable Analysis

DASS-21 covariates for Risk-taking

To examine the possible effect of affective factors in our Risk-taking main findings, we used the same step-wise Multi-level Modelling analysis with final-step models:
nbClicks~XXX+AGE+BMI+GROUP+(1|SUBJ_ID)+(1|Order)
nbClicks~XXX+AGE+BMI+Stimulus*Direction*GROUP+(1|SUBJ_ID)+(1|Order)
where XXX was the relevant Covariate.

Covariate	iv	N	obs	reporting_result
DassDepression	GROUP	71	4034	b_{AN}=-3.3(5.26), t_{AN}=-0.63, b_{RE}=-2.43(4.99), t_{RE}=-0.49, b_{HC_H}=1.45(5.25), t_{HC_H}=0.28, X^2(3)=1.3, p= 0.729, R^2=-0.069, f^2=-0.064

DassDepression	Stimulus x Direction x GROUP	71	4034	b_{AN}=-3.79(2.34), t_{AN}=-1.62, b_{RE}=-1.15(2.38), t_{RE}=-0.48, b_{HC_H}=-3.95(2.56), t_{HC_H}=-1.54, X^2(9)=20.11, **p= 0.017**, R^2=-0.066, f^2=-0.062
DassStress	GROUP	71	4034	b_{AN}=-0.24(5.13), t_{AN}=-0.05, b_{RE}=-1.18(4.9), t_{RE}=-0.24, b_{HC_H}=2.29(5.2), t_{HC_H}=0.44, X^2(3)=0.68, p= 0.877, R^2=-0.057, f^2=-0.054
DassStress	Stimulus x Direction x GROUP	71	4034	b_{AN}=-3.79(2.34), t_{AN}=-1.62, b_{RE}=-1.15(2.38), t_{RE}=-0.48, b_{HC_H}=-3.95(2.56), t_{HC_H}=-1.54, X^2(9)=20.09, **p= 0.017**, R^2=-0.055, f^2=-0.052
DassAnxiety	GROUP	71	4034	b_{AN}=-2.31(4.77), t_{AN}=-0.48, b_{RE}=-1.96(4.88), t_{RE}=-0.4, b_{HC_H}=1.55(5.21), t_{HC_H}=0.3, X^2(3)=1.02, p= 0.795, R^2=-0.066, f^2=-0.062
DassAnxiety	Stimulus x Direction x GROUP	71	4034	b_{AN}=-3.79(2.34), t_{AN}=-1.62, b_{RE}=-1.15(2.38), t_{RE}=-0.48, b_{HC_H}=-3.95(2.56), t_{HC_H}=-1.54, X^2(9)=20.1, **p= 0.017**, R^2=-0.063, f^2=-0.059

We notice that in all cases, the three-way interaction remains statistically significant but the main effect of GROUP does not.

DASS-21 covariates for Hesitance

To examine the possible effect of affective factors in our main Hesitance findings, we used the same step-wise Multi-level Modelling analysis with final-step models:
hesitance~XXX+AGE+BMI+GROUP+(1|SUBJ_ID)+(1|Order)
hesitance~XXX+AGE+BMI+Stimulus*Direction*GROUP+(1|SUBJ_ID)+(1|Order)
where XXX was the relevant Covariate.

Covariate	iv	N	obs	reporting_result
DassDepression	GROUP	71	4031	b_{AN}=676.36(91.23), t_{AN}=7.41, b_{RE}=557.38(86.55), t_{RE}=6.44, b_{HC_H}=73.91(90.93), t_{HC_H}=0.81, X^2(3)=59.09, **p<0.001**, R^2=0.3, f^2=0.428
DassDepression	Stimulus x Direction x GROUP	71	4031	b_{AN}=124.72(60.69), t_{AN}=2.06, b_{RE}=47.67(61.71), t_{RE}=0.77, b_{HC_H}=220.23(66.47), t_{HC_H}=3.31, X^2(9)=33.83, **p<0.001**, R^2=0.302, f^2=0.432
DassStress	GROUP	71	4031	b_{AN}=685.27(89.48), t_{AN}=7.66, b_{RE}=559(85.47), t_{RE}=6.54, b_{HC_H}=78.57(90.66), t_{HC_H}=0.87, X^2(3)=62.29, **p<0.001**, R^2=0.302, f^2=0.432
DassStress	Stimulus x Direction x GROUP	71	4031	b_{AN}=124.7(60.69), t_{AN}=2.05, b_{RE}=47.64(61.71), t_{RE}=0.77, b_{HC_H}=220.24(66.47), t_{HC_H}=3.31, X^2(9)=33.83, **p<0.001**, R^2=0.304, f^2=0.436
DassAnxiety	GROUP	71	4031	b_{AN}=640.81(83.54), t_{AN}=7.67, b_{RE}=541(85.33), t_{RE}=6.34, b_{HC_H}=66.64(91.02), t_{HC_H}=0.73, X^2(3)=62.69, **p<0.001**, R^2=0.297, f^2=0.423

DassAnxiety	Stimulus x Direction x GROUP	71	4031	b_{AN}=124.67(60.69), t_{AN}=2.05, b_{RE}=47.7(61.71), t_{RE}=0.77, b_{HC_H}=220.3(66.47), t_{HC_H}=3.31, X^2(9)=33.84, **p<0.001**, R^2=0.299, f^2=0.427

We notice that in all cases, both the main GROUP effect and the three-way interaction remain statistically significant.

Correlation Matrix (AN&AN-WR)

	avgClicks	avgLastTrialTime	AGE	BMI	EDE_Q_Restrain	EDE_Q_Total	III_Health	III_Health_Conf	III_Health_Clin	III_HopeFear	III_HopeFear_Conf	Dass21_Depression	Dass21_Anxiety	Dass21_Stress
avgClicks	1.00	-0.12	-0.02	-0.02	0.02	0.01	0.03	0.05	-0.02	0.12	0.08	0.05	-0.08	-0.16
avgLastTrialTime	-0.12	1.00	0.07	-0.12	0.14	0.12	-0.07	-0.25	0.11	-0.02	-0.27	0.05	0.09	0.06
AGE	-0.02	0.07	1.00	0.00	-0.14	-0.17	0.09	-0.04	0.14	0.08	0.07	-0.22	-0.13	-0.05
BMI	-0.02	-0.12	0.00	1.00	-0.03	-0.09	-0.67	-0.08	-0.73	-0.08	-0.10	-0.20	-0.09	-0.23
EDE_Q_Restrain	0.02	0.14	-0.14	-0.03	1.00	0.90	-0.03	-0.07	0.22	0.49	-0.02	0.36	0.41	0.27
EDE_Q_Total	0.01	0.12	-0.17	-0.09	0.90	1.00	-0.02	-0.05	0.23	0.50	0.06	0.43	0.47	0.42
III_Health	0.03	-0.07	0.09	-0.67	-0.03	-0.02	1.00	0.25	0.46	0.08	0.18	0.17	0.06	0.11

III_Health_Conf	0.05	-0.25	-0.04	-0.08	-0.07	-0.05	0.25	1.00	-0.12	-0.12	0.63	-0.04	0.20	0.09
III_Health_Clin	-0.02	0.11	0.14	-0.73	0.22	0.23	0.46	-0.12	1.00	0.20	0.01	0.13	-0.06	0.20
III_HopeFear	0.12	-0.02	0.08	-0.08	0.49	0.50	0.08	-0.12	0.20	1.00	-0.08	0.31	0.25	0.22
III_HopeFear_Conf	0.08	-0.27	0.07	-0.10	-0.02	0.06	0.18	0.63	0.01	-0.08	1.00	-0.02	0.20	0.13
Dass21_Depression	0.05	0.05	-0.22	-0.20	0.36	0.43	0.17	-0.04	0.13	0.31	-0.02	1.00	0.74	0.77
Dass21_Anxiety	-0.08	0.09	-0.13	-0.09	0.41	0.47	0.06	0.20	-0.06	0.25	0.20	0.74	1.00	0.66
Dass21_Stress	-0.16	0.06	-0.05	-0.23	0.27	0.42	0.11	0.09	0.20	0.22	0.13	0.77	0.66	1.00

Within-groups Correlations

AN

Correlations:

	avgClicks	hesitance
EDE_Q_Total	-0.02	0.24

p-Values:

	avgClicks	hesitance
EDE_Q_Total	0.90	0.19

AN-WR

Correlations:

	avgClicks	hesitance
EDE_Q_Total	-0.18	-0.13

p-Values:

	avgClicks	hesitance
EDE_Q_Total	0.44	0.58

We note that in each clinical group the overall severity of eating disorder symptomatology (EDE-Q total score) does not correlate strongly or significantly with overall risk taking or hesitance.

EDE-Q Cronbach alpha

AN and *AN-WR*: 0.95

HC-L and *HC-H*: 0.92

HC-L, *AN*, *AN-WR*, *HC-H*: 0.91

SUPERVISED Clustering and Predicting Groups: Binomial Logistic Regression

Supervised Clustering Methods

The aim of this analysis is to predict the Group of a participant based on two "behavioural" measures linked to the *Body Increase* condition (because this condition was expected to have the most clear differences between groups): the model-generated *Prior Probability Of Burst Belief* (*Exploration*) and the overall *Hesitance* (with *AGE* as covariate). Step 1. We created a Logistic Binomial Regression model (*GROUP ~ AGE + BOIN_pBurst_1_L + BOIN_avgLastTrialTime_L*) using as "training" set for the model the

AN and *HC-L* groups. Step 2. We "predicted" the group of the data used to fit the model (*AN* and *HC-L*), for a number of clustering thresholds (called Ratios in the plots). Step 3. We tested the ability of the model to correctly classify individuals as HC or AN (i.e. the prediction success rate) using a different set of data not used to train the model. This comprised the *HC-H*, *HC-Excluded* (i.e. healthy controls who were excluded from our initial selection of *HC-L* and *HC-H* because their BMI was higher than the group median, or their BMI was lower than the median but their EDE-Q restraint score was in the middle two quartiles) and *AN-WR* groups (unfortunately, we did not have a separate group of new acute *AN* patients on which to test the model).

This analysis provides validation to how well our behavioural measures (one directly from BART and the other from the model) can reverse-predict the participant groups. E.g. for threshold 0.45, the model correctly predicts/clusters: 86% of the *AN* as *AN*, and 87% of the *HC-L*, 83% of the *HC-H* and 75% of the *HC-Excluded* as *HC*.

Supervised Clustering Results

The results of the Binomial Logistic Regression were statistically significant for both main predictors, *Prior Probability Of Loss Belief* (*BOIN_pBurst_1_L*) and *Hesitance* (*BOIN_avgLastTrialTime_L*)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-88.01	21.39	-4.12	0.00
AGE	0.09	0.07	1.31	0.19
BOIN_pBurst_1_L	1.86	0.64	2.89	0.00
BOIN_avgLastTrialTime_L	5.84	1.44	4.05	0.00

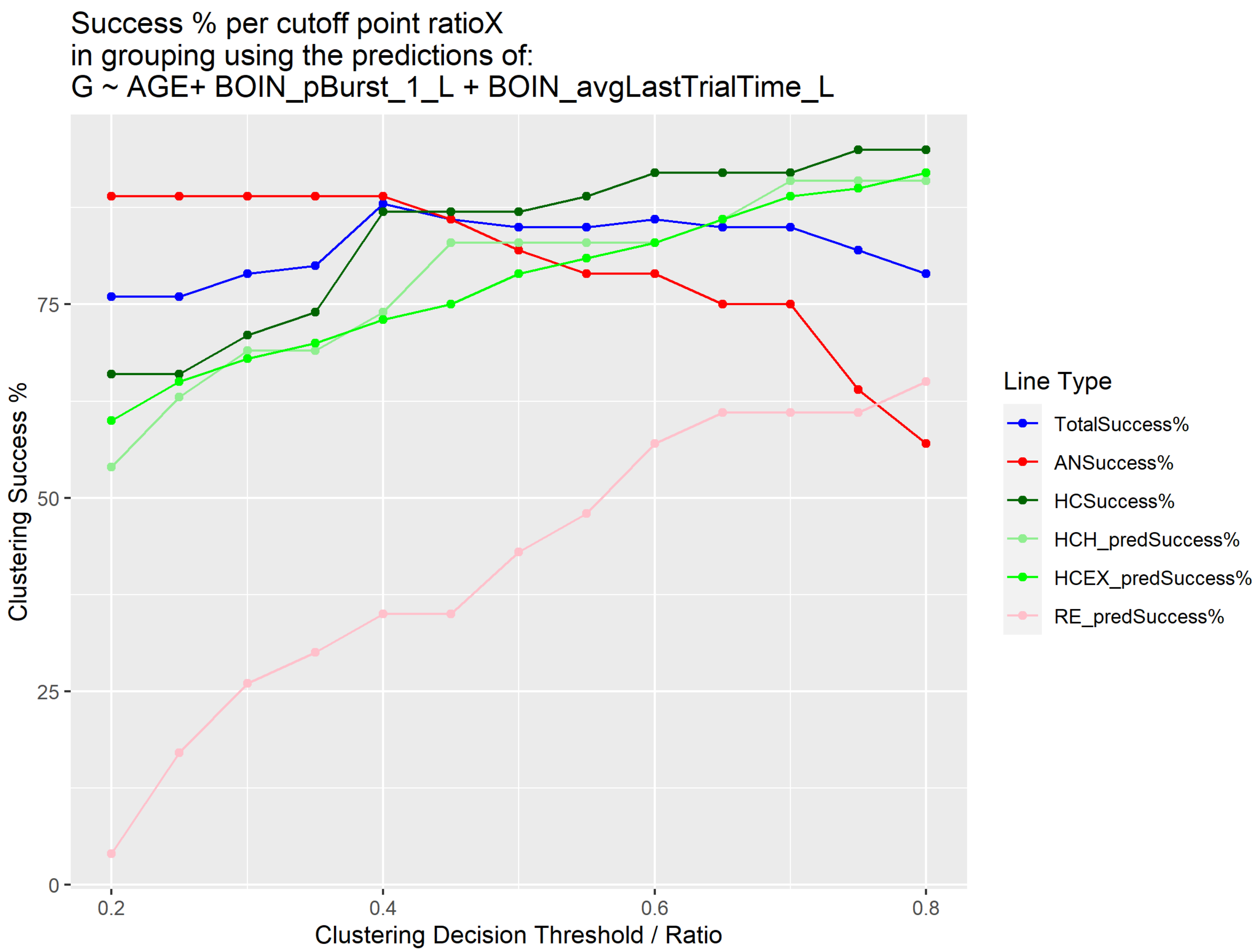
In the table below we display the results of the predictions of the model (classification of participants into Groups), both for the "training" set (*AN* and *HC-L* groups) and for the "testing" sets of *HC-H*, *HC-EXCLUDED* and *AN-WR*:

ratioX	ANpredictedANX	ANpredictedHCX	HCpredictedANX	HCpredictedHCX	HCHpredictedANX	HCHpredictedHCX	SuccessPctX	ANSuccessPctX	HCSuccessPctX	HCHpredicted_success	HCEXpredicted_success	ANWRpredicted_success
0.20	25	3	13	25	16	19	76	89	66	54	60	4
0.25	25	3	13	25	13	22	76	89	66	63	65	17
0.30	25	3	11	27	11	24	79	89	71	69	68	26
0.35	25	3	10	28	11	24	80	89	74	69	70	30
0.40	25	3	5	33	9	26	88	89	87	74	73	35
0.45	24	4	5	33	6	29	86	86	87	83	75	35
0.50	23	5	5	33	6	29	85	82	87	83	79	43
0.55	22	6	4	34	6	29	85	79	89	83	81	48
0.60	22	6	3	35	6	29	86	79	92	83	83	57
0.65	21	7	3	35	5	30	85	75	92	86	86	61
0.70	21	7	3	35	3	32	85	75	92	91	89	61
0.75	18	10	2	36	3	32	82	64	95	91	90	61
0.80	16	12	2	36	3	32	79	57	95	91	92	65

For the “training” set (*AN* and *HC-L*), we notice that for certain threshold values (0.4 to 0.5) the model gave the best percentage predictions (on average higher than 84% prediction success rate). For the threshold range where the “training” set had its higher success (0.4 to 0.5), the “testing” set showed success rates lower than those of the “benchmark” *HC-L*, but in all cases higher than 73%, with *HC-H* being predicted with a higher success rate than *HC-Excluded*, possibly due to the by-definition difference in the *BMI* between the two groups. It was expected that the success rate for *HC-L* would be higher than those of *HC-H* and *HC-Excluded* because the model was not *trained* on the latter two datasets and possibly because of the *BMI* and *EDE-Q Restraint* differences that were used to create the groups in the first place.

Finally, the *AN-WR* group success rate was lower than the success rate in the classification of all the other groups which was expected as *AN* and *HC-L* (not *AN-WR*) were used to create the classification model. For the threshold 0.4 to 0.5, the success rate for the *AN-WR* was between 35% and 43% if they were to be flagged as *HC-L*, and if they were to be flagged as *AN* the success rate was between 65% and 57%.

The analysis above can be visualised in the following plot:



Supplementary Materials 3 - Exploration-Exploitation Cognitive model for the study of Uncertainty in sequential decision making in the Balloon Analogue Risk Task (BART)

Introduction

The model described in this paper is an extension of the *baseline* model described in Wallsten et al.(2005). Their preferred model was the 4-parameter model which best fit the sequential decision making cognitive process during the Balloon Analogue Risk Task (BART) first introduced in (Lejuez et al., 2002). However, that model as well as other models considered in the academic literature (e.g. Wallsten et al.(2005), Van Ravenzwaaij et al.(2011) and Park et al. (2019)), focus on the retrieval of parameters that are primarily related to risk-taking. We are interested in the study of both *risk-taking* and *uncertainty* in sequential decision-making. In this document, we present our modelling for the study of the latter, so we will not consider models focusing on risk-taking.

We hypothesised that in earlier trials participants' decision-making is driven by higher uncertainty and exploration aiming to reduce uncertainty, whereas in later trials, uncertainty has been reduced and it is risk-taking that drives decision-making. Even though this change probably takes place gradually, in this study we assume for simplicity that it takes place at one specific *threshold* moment (trial) and we built our 2-stage model with this assumption in mind. Fitting our 2-stage model allows us to estimate the trial (*threshold*) where a transition from higher uncertainty to lower uncertainty takes place. We call the trials before the threshold *exploration phase/stage* and the trials after the threshold *exploitation phase/stage (*we will be using the terms *phase* and *stage* interchangeably*)*.

To study *uncertainty* in sequential decision-making we have identified two distinct measures, the *coefficient of variation* in clicking and the *hesitance* in the click when collection of earnings takes place. After identification of the transition *threshold*, we compared the uncertainty measures between the two stages. This analysis is presented in the main manuscript of this paper and will not be further discussed in this document.

The purpose of this document is to present the 2-stage model, which allows us to distinguish the 2-stages for each participant and condition.

Going forward, we will be referring to the baseline model of Wallsten et al.(2005) as our *baseline model*.

Model Description

Overview

Our model breaks down the sequence of trials (within each condition, if there is more than one), into two phases, the *exploration* phase and the *exploitation* phase. In line with findings of van Ravenzwaaij et al.(2011), we assume that the DM behaves in each phase as if she believes that the probability of a balloon bursting is constant (*pBelief*). This belief is assumed to be different in the *exploration* versus the *exploitation* phase. Clearly, during the exploration phase this belief (*pBelief*) would not be fixed in practice, but this choice keeps the model simple, allowing it to better retrieve its parameters. In our model, there is a point, a specific trial, where the DM stops *exploring* the environment and starts the *exploitation* phase. We call the specific trial τ (*Threshold*). Upon transition from the *exploration* phase to the *exploitation* phase the main change that takes place is a Belief Update at trial τ regarding the probability of burst $pBelief$ upon each pumping opportunity:

$$pBelief_{exploration} \longrightarrow pBelief_{exploitation}$$

Model Fitting: Maximum Likelihood Estimation

We fitted the model using the Maximum Likelihood Estimation (MLE) method. We write the overall likelihood of the model for each phase (*exploration*, *exploitation*) as the product of the response likelihoods of all pump opportunities in all trials (independence assumption):

$L_{exploration} = \prod_{h=1}^{\tau-1} \prod_{i=1}^{k_h} r_{i,h} (1 - r_{k_h+1,h})^{d_h}$ (4)

$L_{exploitation} = \prod_{h=\tau}^{n} \prod_{i=1}^{k_h} r_{i,h}(1 - r_{k_h+1,h})^{d_h}$ (5)

Where τ is the *threshold* when the transition from *exploration* to *exploitation* takes place, *n* is the total number of trials (per condition), k_h is the total number of pumps the DM made on trial *h*, and d_h=1 if the DM collected trial *h* at $k_h + 1$, or d_h=0 if the trial ended with a burst. In formulas (4) and (5), $r_{i,j}$ is considered to be fixed to $1 - pBelief_{exploration}$ or $1 - pBelief_{exploitation}$ depending on the phase. It can be shown (Wallsten et al.(2005)) that under these conditions, equations (4) and (5) have a closed form solution with respect to $pBelief$ that maximises them and that in each phase:

$$pBelief_{phase} = \frac{\sum_{h=1}^{n_{phase}} nbPumps_h}{\sum_{h=1}^{n_{phase}} nbPumps_h + \sum_{h=1}^{n_{phase}} d_h}$$

To be able to compare our model with the *benchmark model*, we computed the Logarithm of equations (4) and (5), because sums of very small quantities are more manageable than products.

The optimal *threshold* τ was computed by evaluating the MLE for each possible value of this *threshold*, i.e. from 1 to *n,* and finally selecting the parameter set ($pBelief_{exploration}$, $pBelief_{exploitation}$, τ) that gave the most optimal log-likelihood.

Notice that we calculated one parameter set ($pBelief_{exploration}$, $pBelief_{exploitation}$, τ) for each condition the participant ran.

Parameter Recovery and Comparison with the Baseline model

The results of this section are based on the data of subclinical study S2. Both the *Baseline* model and our 2-stage model retrieve their best-fit parameters via closed form solutions, therefore they both have no issues retrieving their parameters.

Comparing the goodness of fit (using the Maximum Log Likelihood, the AIC and the BIC), we found that for all criteria the 2-stage model had a consistently better fit comparing to the *baseline model* across all conditions and overall.

		2-stages Model				**Baseline Model**			
Condition	**N**	**MLE**	**AvgMLE**	**AIC**	**BIC**	**MLE**	**AvgMLE**	**AIC**	**BIC**
BalloonDecrease	318	-19,609	- 61.7	39,222	39,230	-19,817	- 62.3	39,636	39,640
BalloonIncrease	317	-19,445	- 61.3	38,893	38,901	-19,651	- 62.0	39,303	39,307
BodyDecrease	318	-19,881	- 62.5	39,766	39,774	-20,083	- 63.2	40,168	40,172
BodyIncrease	318	-19,475	- 61.2	38,955	38,962	-19,684	- 61.9	39,369	39,373
TOTAL	1271	-78,410	- 61.7	**156,825**	**156,835**	-79,235	- 62.3	**158,471**	**158,476**

Note 1: In all models and measures of fit, the Body Decrease condition seems to have a slightly worse fit than the other conditions.

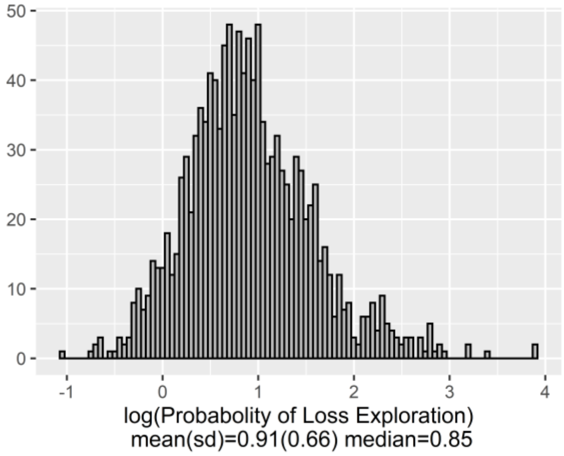
Note 2: In AIC and BIC, we used *k*=1 parameter for the baseline model and *k*=2 parameters for the 2-stages model.

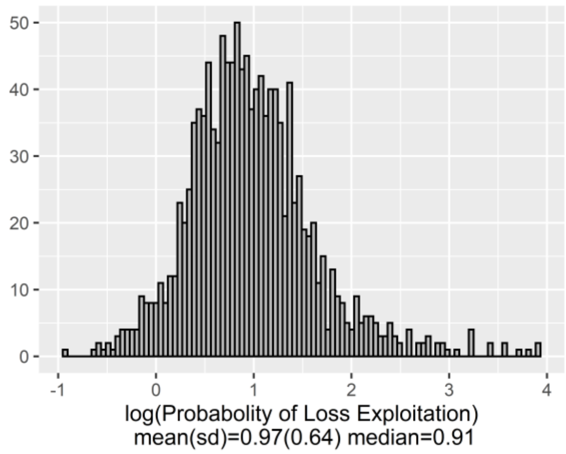
In the following table we present the log-likelihood per pump and per collection for each of the four conditions:

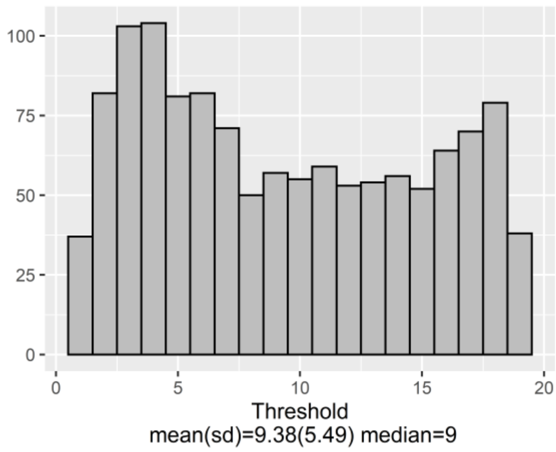
Condition	**LL stage 1 per pump**	**LL stage 2 per pump**	**LL stage 1 per collection**	**LL stage 2 per collection**
BalloonDecrease	0.032	0.033	3.88	3.76
BalloonIncrease	0.031	0.036	3.84	3.72
BodyDecrease	0.037	0.039	3.82	3.66
BodyIncrease	0.035	0.038	3.79	3.68

Note: Columns *LL stage 1 per pump* and *LL stage 2 per pump* display the average across all participants and trials log-likelihood per pump for each one of the conditions. We see that in all conditions stage 1 has a better fit. Columns *LL* *stage 1 per collection* and *LL stage 2 per collection*, display the average across all participants and trials log-likelihood per collection click for each one of the conditions.

Recovered Parameters Summary (non-Clinical)





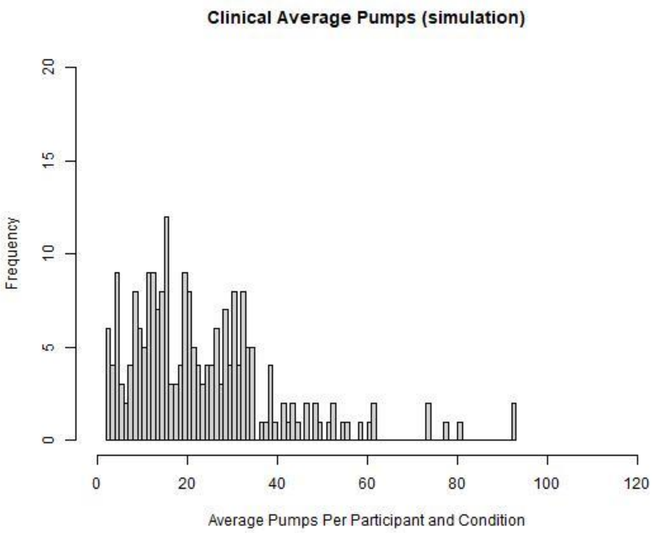


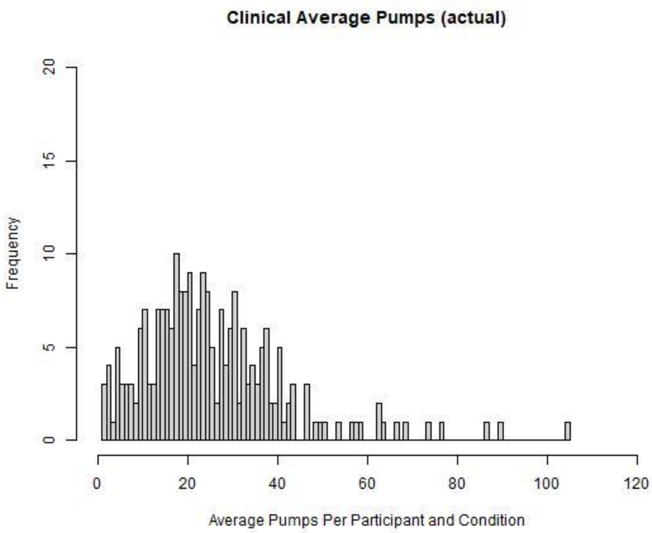
Simulated\Predicted versus Actual Pumps

Overview and Methodology

We used the recovered Probabilities of Burst Belief (Exploration and Exploitation stages) and Threshold per participant and condition and simulated the relevant trials. We assumed that the participant made in advance the decision to collect on the number of pumps where the cumulative Probability of Burst Belief was higher than 50%.

Clinical Study





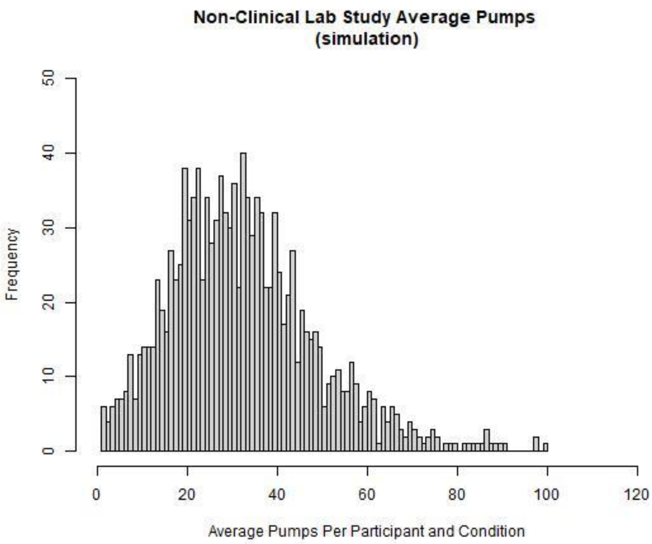
Actual Pumps Summary

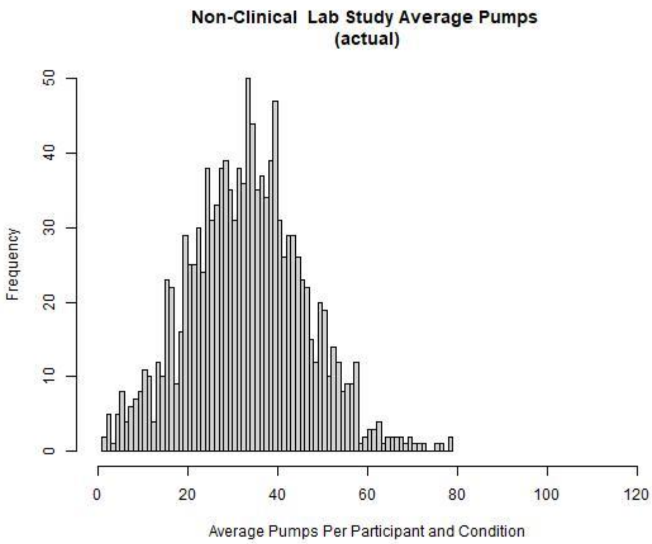
```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.00   15.12   22.88   25.54   32.87  104.50
```

Simulated Pumps Summary

```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.00   11.91   19.90   23.42   30.99   92.20
```

Non-Clinical Study





Actual Pumps Summary

```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.00   24.48   33.33   33.31   41.63   78.50
```

Simulated Pumps Summary

```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.00   21.00   30.68   32.52   41.55  100.55
```

Summary

We can see in the histograms and summary statistics above that the simulated trials follow closely the actual participant performance, as the actual Probabilities of Burst Beliefs and Thresholds were used as “seeds” for the simulated results. We notice that our simulated/predicted pumps follow a distribution that has a slightly stronger right skew than the actual pumps distribution.

Discussion

Comparing to the 4-parameter model of Wallsten et al.(2005), we do not model the DMs' initial belief for the probability of a trial bursting upon a pump, and its evolution. This belief is computed directly from the empirical data, whereas Wallsten et al.(2005) use 2 parameters to model it. The learning and evolution in probability *pBelief*, in our model, is defined by the *threshold* τ, which in this way is a measure of how fast, if at all, the DM completes the *exploration* phase and moves to the *exploitation* one. In practice, it is very likely that the belief evolution during the *exploration* phase takes place gradually and not in one jump/step as we model it. We hope future work on our model could lead to an improvement that would capture such a feature. Finally, future work could lead to a model combining the 2-stage approach of our model with a version of the 4-parameter model, which would allow us to examine the evolution of the recovered parameters from the *exploration* to the *exploitation* phase.

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Supplementary Materials 4 - Cognitive model analysis of Risk-taking during sequential decision making in the Balloon Analogue Risk Task (BART)

Introduction

The model used in this paper is the Exponential-Weight Model (EW model) by Park et al. (2019), an extension of the models described in Wallsten et al.(2005). The Wallsten et al.(2005) preferred model was the 4-parameter model which best fit the sequential decision making cognitive process during the Balloon Analogue Risk Task (BART) first introduced in (Lejuez et al., 2002). The 4-parameter model combines *learning* with *evaluation*. *Learning* is assumed to take place before each trial to update the DM's (Decision Maker's) belief of the probability of a burst. Defined within the framework of Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), *evaluation* is on the expected gains and it is used to make a choice between the options of pumping or stopping. In their winner/best model, the evaluation takes place prior to the trial and is used to identify the optimal number of pumps in the specific trial.

Nevertheless, it has been shown (van Ravenzwaaij et al., 2011) that this model does not retrieve its *learning* parameters sufficiently, which also has a negative effect on the recovery of the other parameters. Van Ravenzwaaij et al.(2011) showed that a 2-parameter model which assumes the DM has a fixed belief for the probability of burst (i.e. no *learning*) manages to retrieve its parameters better. It should be noted that this was shown in a version of BART which had a fixed probability of burst and where the DMs were informed of this fixed probability in advance.

The Exponential-Weight Model (EW model) developed by Park et al. (2019) was shown by the authors to address the issues of the 4-parameter model, while being applied to the original version of BART. There are three main differences between the EW model and the original 4-parameter model. The first is in the way the initial and subsequent beliefs regarding the probability of explosion update from trial to trial. The second is in the fact that the 4-parameter model assumes that the evaluation of rewards takes place before the start of the trial, whereas the EW model assumes it takes place on a click-by-click basis. Finally, the third difference is the inclusion in the EW model of a fifth parameter, *Loss Aversion*, which weighs the temporary earnings within a trial against the reward of one additional click.

Notice1: Park et al. (2019) most recently (24/12/2020) included in their pre-print a model (Exponential-Weight Mean-Variance Model) which seemed to fit data even better than the Exponential-Weight Model. However, that model was made publicly available after we had completed our analysis and will therefore not be considered in this study.

Notice 2: For the implementation of both the 4-parameter and the EW models, we used and created our own adaptation of the code of R package hBayesDM (Ahn et al. (2017)). This also means that we used Bayesian parameter recovery.

Model Parameters and their Meaning

The parameters of the two models are best explained in their original papers. Here we simple present an overview. The parameters of most interest in our study of risk-taking are γ^+ of the 4-parameters model and ρ & λ of the Exponential-Weight (EW) model.

EW Model

ρ (rho): Risk Aversion (Park et al. (2019) call this variable Risk Preference but interpret it as Risk Aversion)

λ (lambda): Loss Aversion

τ (tau): Inverse Temperature, indicating how deterministic (higher values) or random the choice is

φ (phi): The initial probability of burst belief

η (eta): Updating Exponent (for the update of the probability of burst belief)

4-parameter model

$\boldsymbol{\gamma^+}$ (gamma): Risk-Taking

τ (tau): Inverse Temperature

m0/a0 (phi): The initial probability of burst belief. For all practical purposes we are not really interested in each of these two parameters individually, but in their ratio.

Model Comparison

The results of this section are based on the data of subclinical study S2.

Comparing the goodness of fit (using the Maximum Log Likelihood, the AIC and the BIC) we found that, in line with the findings of Park et al. (2019), for all criteria the Exponential-Weight model had a consistently better fit comparing to the 4-parameter model across all conditions.

		Exponential-Weight Model				**4-parameter Model**			
Condition	**N**	**MLE**	**MLE_AVG**	**AIC**	**BIC**	**MLE**	**MLE_AVG**	**AIC**	**BIC**
BalloonDeflate	318.00	- 14,429	- 45.4	28,863	28,916	- 14,687	- 46.2	29,377	29,419
BalloonInflate	318.00	- 14,330	- 45.1	28,664	28,717	- 14,526	- 45.7	29,057	29,099
BodyDeflate	318.00	- 14,598	- 45.9	29,201	29,254	- 14,900	- 46.9	29,803	29,845
BodyInflate	318.00	- 14,264	- 44.9	28,533	28,586	- 14,512	- 45.6	29,027	29,069
Total	**1,272.00**	**- 57,621**	**- 45.3**	**115,261**	**115,473**	**- 58,625**	**- 46.1**	**117,264**	**117,432**

Note 1: In both models and all measures of fit, the Body Deflate condition seems to have a slightly worse fit than the other conditions, whereas the Body Inflate condition seems to have a slightly better fit than the other conditions.

Note 2: In AIC and BIC, we used k=5 parameters for the Exponential-Weight model, k=4 parameters for the 4-parameter model.

Recovered Parameters Correlations (non-Clinical S2)

Correlations between EW model parameters

	phi	**rho**	**eta**	**lambda**	**tau**
phi		-0.55	-0.09	-0.2	0.06
rho	-0.55		0.07	-0.19	0.08
eta	-0.09	0.07		-0.12	-0.03
lambda	-0.2	-0.19	-0.12		-0.06
tau	0.06	0.08	-0.03	-0.06	

Notice 1: The correlation between phi and rho is relatively high (-0.55). We cannot be certain about the roots of this, but it could be a cause for concern in terms of the independence of the recovery for these two parameters.

Notice 2: There is some correlation between rho and lambda (-0.19) but this is relatively small.

Correlations between 4-parameters model parameters

	a0	**m0**	**gamma**	**tau**
a0		0.93	-0.17	0.65
m0	0.93		-0.05	0.79
gamma	-0.17	-0.05		-0.16
tau	0.65	0.79	-0.16	

Notice 1: As noted by the original authors, Wallsten et al.(2005), as well as subsequent research (e.g. van Ravenzwaaij et al., 2011) and Park et al. (2019)), there is significant correlation between a0 and m0, indicating that the recovery of each of these parameters is not independent and looking at the specific values could be problematic. However, for all practical purposes we are interested in the ratio m0/a0, which does not seem to be negatively affected by the correlation between the two variables (see next section).

Correlations between risk-specific model parameters and EDE-Q-Restraint

	EDE Q Restraint	**EW rho**	**EW lambda**	**EW phi**	**par4 phi**	**par4 gamma**
EDE Q Restraint		-0.18	0.02	0.12	0.03	-0.01

EW rho	-0.18		-0.19	-0.55	-0.13	-0.27
EW lambda	0.02	-0.19		-0.2	-0.2	-0.37
EW phi	0.12	-0.55	-0.2		0.4	0.03
par4 phi	0.03	-0.13	-0.2	0.4		0.21
par4 gamma	-0.01	-0.27	-0.37	0.03	0.21	

Notice 1: As noted by Park et al. (2019), these is negative correlation between EW rho and the 4-parameter gamma (-0.27). This is why they call their rho parameter *Risk Aversion* and this is the terminology we followed in the main manuscript of this paper.

Discussion

The Exponential-Weight (EW) model fit the data better than the 4-parameter model across all comparison measures and conditions. The fit for both models was relatively good and the difference between the two was relatively small (comparing to the fit of the baseline and the 2-stage model we present in our document studying Uncertainty in BART).

Regarding parameter recovery, we reproduced the findings of the original authors, which identified issues with the recovery of some of the parameters, however, similar to their findings, we saw in the previous sections that the parameters of interest in our study ($\gamma^+$of the 4-parameter model and ρ & λ of the EW model) are relatively reliable.

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