Computational modeling of epiphany learning

Chen et al. 10.1073/pnas.1618161114

Supporting Information (SI)

SI Method: Eye Tracking. Subjects' left-eye fixation patterns and pupil diameter were recorded at 1000 Hz using an Eyelink 1000 Plus (SR Research, Osgoode, ON, Canada) eye-tracker, located 40.5 cm in front of the subject. We used a chinrest provided by the manufacturer to minimize head movement. Stimuli were presented on an LCD monitor (24' XL2420TE, BenQ), located 79 cm in front of the subject, in an otherwise dark room. Before the experiment started, subjects went through a standard nine-dot calibration procedure provided by the eye tracker's manufacturer.

SI Method: Stimuli. Stimulus presentation was implemented in Matlab, with its Psychtoolbox and Eyelink toolbox extensions (1–3) with a resolution of 1920 × 1080. All colors used in the experiment had the same 15 cd/m^2 luminance. The 11 choice numbers were located in 11 circles, each with a radius equal to 4% of the width of the monitor (53 cm), evenly distributed on a bigger circle with a radius equal to 40% of the length of the monitor (30 cm) and centered on the monitor. The numbers always increased in a clockwise direction, but the exact positions were randomized across trials.

SI Method: Data Analysis.

Model fitting. Models were fit by matching the predicted probability of choosing 0 on each trial (up to the commit trial) with the observed data, using maximum likelihood estimation. Specifically, we used the quasi-newton method with $11 \times 15 = 165$ (EL model, $q_1 \times d$) or $11 \times 4 \times 13 = 572$ (RL model, $\lambda \times \phi \times A_1(0)$) starting points to search for optimal parameter combinations under the following constraints: EL : $0 < q_1, q_2 < 1$; RL: $0 < \phi < 1, -60 < A_1(0) < 60$ and $0 < \lambda < 40$ Note that $1/d$ is only identified up to an integer scale, so we performed these searches using every possible value of $1/d$ from 1 to 15. Also, we only varied the starting point for q_1 and d, but not q_2. This is because given any combination of q_1 and d, the q_2 that maximizes the likelihood function is unique, and can be easily found by the algorithm due to the concavity of the likelihood function. Moreover, we did not constrain $q_1 < q_2$. However, this constraint was only violated in 5 subjects (all Commit > 0 subjects). The only analysis this impacts is the $ev(t-1)$ regression (Table S4), and when we re-run that analysis with the constraint, we find no qualitative differences, i.e. no changes in terms of significance. Here, all parameters are estimated separately for each subject.

ROI definitions. The ROIs for the 11 numbers and the yes and no button were defined as circles (for numbers) and rectangles (for buttons and text) slightly (30 and 50%) larger in diameter than they appeared on the screen.

Preprocessing of pupil data. Periods of full blinks were detected using a standard algorithms provided by the manufacturer, and partial blinks were detected by the presence of out-of-screen fixations. Both type of blinks were removed by linear interpolation of pupil diameter between 100 ms before and after each blink. The pupil data were then processed by a 5 Hz low-pass filter, and corrected for pupil foreshortening error (4). After that, the percentage change in pupil diameter was calculated based on a 1000 ms baseline pupil diameter immediately before the feedback screen.

Choice comparison between behavioral and eye-tracking experiments. In the main text we describe how subjects in the eye-tracking experiment played against randomly selected rounds from the behavioral experiment in order to prevent them from noticing decreasing trends in the choices of their opponents. It is worth asking whether this change had any effect on subjects' choices. We indeed found that in round 10, only 46% of the eye-tracking subjects chose zero, compared to 82% in our behavioral experiment. Thus it appears that our design had the desired effect of reducing learning of the optimal strategy. Of course, other differences between the experiments may also have contributed to this effect.

Extensions of the EL/RL Model. Here we discuss three possible extensions to the EL model. Some of these extensions can be applied to the RL model as well.

Generalization (Model G). The EL model we've presented has the restriction that $X_0 = \{0\}$, that is, the only winning number that promotes an epiphany is 0. It is possible that winning with other low numbers promotes the epiphany. In the learning literature, outcomes associated with a particular stimulus become associated with other similar stimuli. This is known as generalization (5). With this in mind, we considered an extension of the EL model where $X_0 \equiv \{0, 1, 2, \ldots, K\}$ and $X_1 \equiv \{K+1, \ldots, 10\}$, where K is a free parameter. We also extend the RL model in the same way. In this way, we allow other low numbers to provide evidence for 0.

Negative epiphanies (Model N). Our EL model only allows for an epiphany on the optimal strategy. However, it is possible that a suboptimal strategy could give enough positive feedback to lead the subject to an incorrect belief that this strategy is optimal. Therefore, an alternative way to model epiphanies is to allow for a different epiphany when the accumulated evidence crosses the negative threshold (-1). Specifically, this model uses the same rule for evidence accumulation and choice probability as in the original model, except that whenever $ev(t)$ hits -1, the subject begins to choose 0 with probability $(1 - q_2)/10$, until a different epiphany occurs.

Any epiphany (Model A). Another way to allow other epiphanies to occur is to remove the restriction that epiphanies occur for 0 or "not 0", and instead define $X_0 = \{c\}$ and $X_1 = \{0, \ldots, c-1, c+1, \ldots, 10\}$, where c is a free parameter (typically the number the subject committed to in the end). Note that this model is equivalent to the one in the main text when $c = 0$. In this case the model specifies the probability of choosing c and the other numbers in the same way as in the original EL model. We can modify the RL model in the same way.

Model comparisons. Note that each of these extensions can be mixed and matched to produce different versions of the EL and RL models (with the exception of extension N to RL). This leaves us with seven alternative models for EL and three for RL. We compared these ten models with the original EL and RL model from the text using the Bayesian information criterion (BIC, see Table S1). While adding generalization (G) provided a better fit for commit-to-0 subjects, it did the opposite for the other two groups. The other two extensions did not help with any group. Importantly, the EL models continued to outperform the RL models in all cases.

1. Pelli DG (1997) The VideoToolbox software for visual psychophysics: transforming numbers into movies. *Spatial Vision* 10(4):437–442.
2. Brainard D (1997) The psychophysics toolbox. *Spatial Vision* 10(4):433–436.
3. Kleiner M, Brainard D, Pelli D (2007) *What's new in Psychtoolbox-3?* (Perception 36 ECVP Abstract Supplement.).
4. Hayes TR, Petrov AA (2015) Pupil diameter tracks the exploration-exploitation tradeoff during analogical reasoning and explains individual differences in fluid intelligence. *Journal of Cognitive Neuroscience* 28(2):308–318.
5. Pearce JM (1987) A model for stimulus generalization in pavlovian conditioning. *Psychological review* 94(1):61.

Chen et al. 10.1073/pnas.1618161114

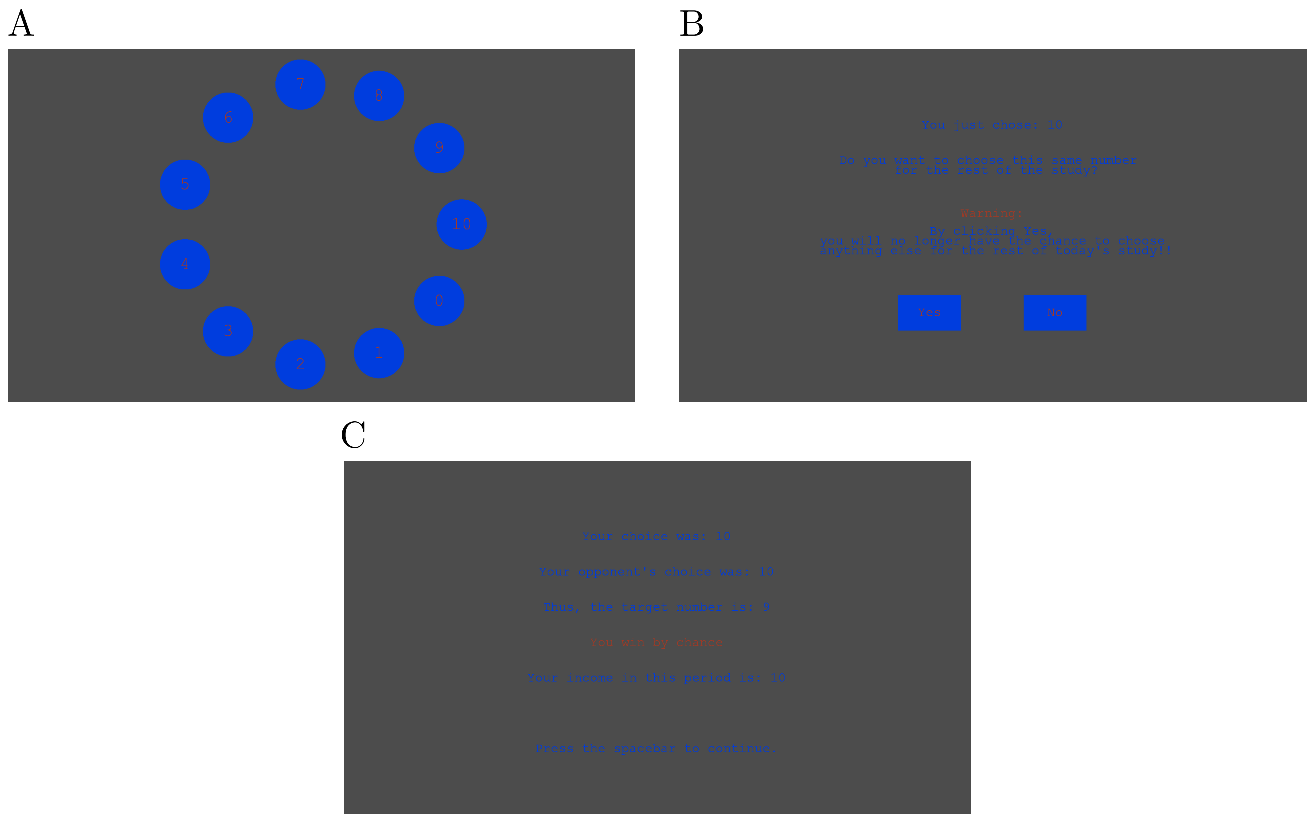

Fig. S1. Eye-tracking experiment. (*A*) Choice screen. Subjects chose an integer from 0 to 10. (*B*) Commitment screen. Subjects chose whether to commit to their chosen number for the remainder of the study. (*C*) Feedback screen. Subjects saw their chosen number, their opponent's chosen number, the target number, the game outcome, and the resulting earnings.

Table S1. BIC model comparison of EL and RL models. Each model is characterized by the presence or absence of each of the three extensions: G = generalization, N = negative epiphany, A = any epiphany. For example, model GN_ is the model with generalization and the possibility of a negative epiphany. ___ is the model from the main text with no extensions.

Model	EL								RL			
	GN_	GNA	_N_	_NA	G__	G_A	___	__A	G__	G_A	___	__A
Commit-to-0	105.52	–	112.34	–	103.79	–	109.94	–	165.96	–	173.63	–
Commit $>$ 0	52.09	257.21	49.20	271.03	52.09	70.38	49.20	98.46	67.35	197.72	67.23	258.19
No Commit	189.65	–	187.90	–	189.65	–	187.77	–	228.35	–	231.13	–

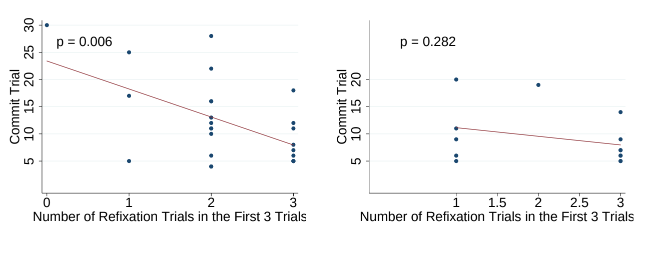

Fig. S2. Refixations in the first three trials. Commit trial as a function of the number of trials with refixations in the first three trials, for (*Left*) commit-to-0 subjects and (*Right*) commit $>$ 0 subjects. p-values indicate significance for Pearson correlations. Here we exclude all subjects who committed in trial 2, because we require at least three decision trials. We obtain very similar results using the first 2, 4, or 5 trials to compute the refixation measure: the p-values are 0.016 v.s 0.291, 0.071 v.s 0.423 and 0.098 v.s 0.668 for the commit-to-0 and commit $>$ 0 groups respectively.

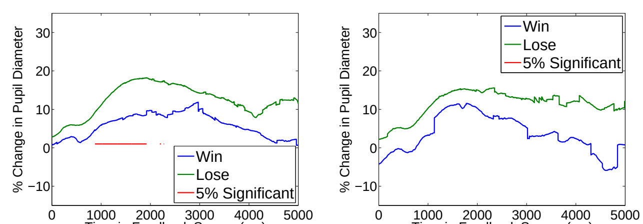

Fig. S3. Pupillary responses. Change in pupil diameter on the feedback screen for wins and losses for all trials before the commit trial, for subjects who (*Left*) committed to 0, and (*Right*) committed to other numbers. Red horizontal bars indicate significant differences between wins and losses at $p < 0.05$.

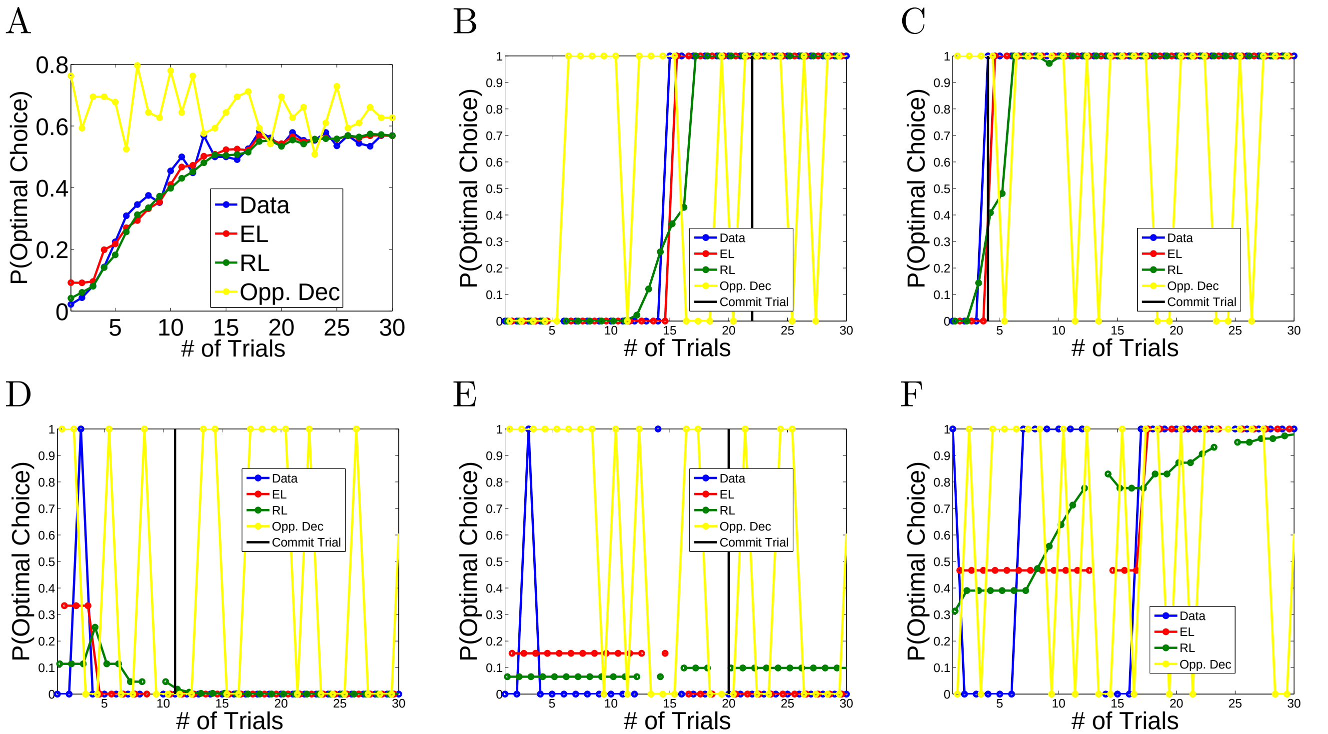

Fig. S4. Comparing EL and RL. Red and green lines are best fit curves from the EL and RL model respectively, and yellow curves are opponent's choices. (*A*) Aggregated data (n=59). Learning appears gradual and is similarly well fit by EL and RL. (*B-F*) Individual data from five representative subjects (subject # 10,16 ,8 ,58 and 23, one per panel). The first two committed to 0; the second two committed to other numbers, and the last one did not commit.

Fig. S5. Database experiment. (*A*) Choice screen. Subjects chose an integer from 0 to 10. (*B*) Commitment screen. Subjects chose whether to commit to their chosen number for the remainder of the study. (*C*) Feedback screen. Subjects saw their chosen number, their opponent's chosen number, the target number, the game outcome, and the resulting earnings.

Table S2. K-S test for sudden jumps.

Subject	Commit	Change	K-S	Choose-0 rate		K-S	Model
id	number	point	p-value	before	after	EL	EL
1	4	29	100%	0%	0%	0	0
2	10	29	100%	0%	0%	0	0
3	0	12	0%	25%	89%	1	1
4	0	3	0%	0%	100%	1	0
5	0	1	10%	0%	100%	0	1
6	0	5	0%	0%	100%	1	1
7	–	29	100%	0%	0%	0	0
8	1	3	85%	33%	0%	0	1
9	7	29	100%	0%	0%	0	0
10	0	14	0%	0%	100%	1	1
11	0	7	0%	14%	100%	1	1
12	3	29	100%	0%	0%	0	0
13	0	2	1%	0%	100%	1	1
14	7	29	100%	0%	0%	0	0
15	0	3	0%	0%	100%	1	1
16	0	3	0%	0%	100%	1	1
17	0	5	0%	0%	84%	1	1
18	0	6	0%	0%	96%	1	1
19	0	9	0%	22%	100%	1	1
20	0	11	0%	0%	95%	1	1
21	0	10	0%	0%	90%	1	1
22	0	4	0%	0%	96%	1	1
23	–	6	3%	17%	79%	1	1
24	–	10	0%	0%	95%	1	1
25	–	13	0%	0%	94%	1	1
26	0	4	0%	0%	100%	1	1
27	–	19	0%	0%	100%	1	1
28	7	29	100%	0%	0%	0	0
29	–	5	6%	0%	60%	0	1
30	2	29	100%	0%	0%	0	0
31	–	6	1%	0%	67%	1	1
32	4	29	100%	0%	0%	0	0
33	7	29	100%	0%	0%	0	0
34	–	28	7%	18%	100%	0	1
35	6	29	100%	0%	0%	0	0
36	0	4	0%	0%	92%	1	0
37	0	9	0%	0%	90%	1	1
38	0	3	0%	0%	100%	1	1
39	0	5	0%	20%	100%	1	1
40	0	7	0%	0%	78%	1	1
41	–	9	60%	0%	29%	0	1
42	4	29	100%	0%	0%	0	0
43	0	10	0%	10%	100%	1	1
44	8	29	100%	0%	0%	0	0
45	2	13	100%	8%	0%	0	1
46	1	8	100%	13%	0%	0	1
47	6	29	100%	0%	0%	0	0
48	–	17	0%	0%	77%	1	1
49	0	5	0%	0%	100%	1	1
50	2	29	100%	0%	0%	0	0
51	2	13	77%	23%	0%	0	1
52	–	13	17%	38%	0%	0	1
53	4	29	100%	0%	0%	0	0
54	0	9	0%	22%	100%	1	1
55	5	29	100%	0%	0%	0	0
56	–	6	0%	0%	88%	1	1
57	5	3	93%	33%	4%	0	1
58	6	29	100%	0%	0%	0	0
59	0	10	0%	20%	100%	1	1

Table S3. Probit regression with the dependent variable equal to 1 if in a given trial the subject chose the number that they later committed to, and 0 otherwise. The variable *Trials to Commit* is 0 for the commit trial, -1 for the preceding trial, -2 for the trial before that, etc., and the variable *Commit* $>$ *0* is a dummy variable indicating whether the subject committed to a number greater than 0 (=1), or committed to 0 (=0). Subjects who did not commit at all or who committed in the first possible trial (trial 2) were excluded from this analysis. The model included clustered standard errors to account for repeated observations per subject.

	Chose Commit #
Trials to Commit	0.124***
	(0.000)
Commit $>$ 0	-2.069***
	(0.000)
Commit $>$ 0 $\times$ Trials to Commit	-0.122**
	(0.023)
Constant	0.344
	(0.105)
Observations	399
Number of subjects	40

Probit model with clustered s.e., p-value in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Chen et al. 10.1073/pnas.1618161114

Table S4. Linear regressions with the dependent variable equal to the percentage of dwell time on 0 in the choice screen. The variable $ev(t-1)$ is equal to the current evidence for the optimal strategy according to the EL model, $A_0(t-1)$ is equal to the current evidence for the optimal strategy according to the RL model, *Commit > 0* and *No Commit* are dummy variables for subjects who committed to a number greater than 0, did not commit at all, or committed to 0 (=0 for both), and *Total Win Trials* is equal to the number of times the subject has won the game up to that point. Regressions (2), (4) and (6) includes only trials where the subject did not choose the number that they later committed to. The model included clustered standard errors to account for repeated observations per subject.

	(1)	(2)	(3)	(4)	(5)	(6)
	% of Dwell Time on 0					
$ev(t-1)$	15.94***	16.99***	17.67***	20.46***	15.66***	10.83***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Commit $>$ 0	-1.191	12.48**	-0.276	14.11***	-1.808	9.304**
	(0.801)	(0.011)	(0.958)	(0.007)	(0.692)	(0.035)
No Commit	9.131**	21.07***	2.329	14.65***	5.440	15.45***
	(0.041)	(0.000)	(0.602)	(0.000)	(0.249)	(0.000)
Commit $>$ 0 $\times$ $ev(t-1)$	-20.42***	-22.39***	-21.86***	-25.26***	-18.85***	-14.41***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
No Commit $\times$ $ev(t-1)$	-15.06***	-16.11***	-18.37***	-21.16***	-14.87***	-10.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Total Win Trials			-0.803	-1.914		
			(0.519)	(0.421)		
Commit $>$ 0 $\times$ Total Win Trials			-0.107	0.226		
			(0.955)	(0.936)		
No Commit $\times$ Total Win Trials			3.348**	4.459*		
			(0.013)	(0.066)		
$A_0(t-1)$					0.00876	0.631***
					(0.949)	(0.000)
Commit $>$ 0 $\times$ $A_0(t-1)$					0.334	-0.395
					(0.530)	(0.621)
No Commit $\times$ $A_0(t-1)$					0.400***	-0.222
					(0.006)	(0.230)
Constant	13.12***	1.177	12.64***	0.313	12.70***	2.686
	(0.000)	(0.516)	(0.000)	(0.880)	(0.000)	(0.229)
Observations	644	496	644	496	540	419
Number of subjects	58	51	58	51	57	50

Linear model with clustered s.e., p-value in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Table S5. Linear regressions with the dependent variable equal to the percentage of dwell time on the yes button on the commitment screen. The variable *Trials to Commit* is 0 for the commit trial, -1 for the preceding trial, -2 for the trial before that, etc., *Is Commit Trial* is equal to 1 if the subject committed on this trial (0 otherwise), and *Commit $>$ 0* and *Commit-to-0* are dummy variables for subjects who committed to a number greater than 0 or committed to 0. The model included clustered standard errors to account for repeated observations per subject.

	(1)	(2)
	% of Dwell Time on the Yes Button	
Trials to Commit	-0.0461	0.347**
	(0.626)	(0.042)
Commit $>$ 0	0.289	
	(0.916)	
Commit $>$ 0 $\times$ Trials to Commit	0.393**	
	(0.044)	
Is Commit Trial	60.66***	46.82***
	(0.000)	(0.000)
Is Commit Trial $\times$ Commit $>$ 0	-13.84**	
	(0.036)	
Chose Commit #	-0.225	-3.268*
	(0.835)	(0.061)
Chose Commit # $\times$ Commit $>$ 0	-3.043	
	(0.138)	
Commit-to-0		-0.289
		(0.916)
Commit-to-0 $\times$ Trials to Commit		-0.393**
		(0.044)
Is Commit Trial $\times$ Commit-to-0		13.84**
		(0.036)
Chose Commit # $\times$ Commit-to-0		3.043
		(0.138)
Constant	2.528**	2.817
	(0.022)	(0.263)
Observations	344	344
Number of subjects	47	47

Linear model with clustered s.e., p-value in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Table S6. Linear regressions with the dependent variable equal to the percentage of dwell time on (1) the opponent's choice or (2) the game result, on the feedback screen. The variable *Trials to Commit* is 0 for the commit trial, -1 for the preceding trial, -2 for the trial before that, etc., *Is Commit Trial - 1* is equal to 1 if the subject committed on the following trial (0 otherwise), and the variable *Commit $>$ 0* is a dummy variable indicating whether the subject committed to a number greater than 0 (=1), or committed to 0 (=0). *Chose Commit #* is a dummy variable indicating whether the subject chose the commit number she later commit to (=1), or did not choose (=0). *Opp. Choice is Commit #* is a dummy variable indicating whether the opponent chose the commit number the subject later commit to (=1), or did not choose (=0). Subjects who did not commit at all were excluded from this analysis. The model included clustered standard errors to account for repeated observations per subject.

	(1)	(2)	(3)
	% of Dwell Time on		
	Opponent's Choice		Results
Trials to Commit	-0.0756	-0.0647	0.503***
	(0.637)	(0.680)	(0.003)
Commit $>$ 0	6.022	2.488	-4.655
	(0.207)	(0.634)	(0.353)
Commit $>$ 0 $\times$ Trials to Commit	0.823**	0.780**	-0.860**
	(0.013)	(0.017)	(0.029)
Is Commit Trial - 1	-1.259	-1.111	2.701
	(0.646)	(0.685)	(0.538)
Is Commit Trial - 1 $\times$ Commit $>$ 0	-1.858	-1.377	-4.991
	(0.716)	(0.780)	(0.409)
Chose Commit #	-4.589*	-5.185*	11.55***
	(0.089)	(0.066)	(0.000)
Chose Commit # $\times$ Commit $>$ 0	5.051	6.126	-13.85***
	(0.251)	(0.169)	(0.000)
Opp. Choice is Commit #		-3.132	
		(0.147)	
Opp. Choice is Commit # $\times$ Commit $>$ 0		12.44***	
		(0.004)	
Constant	18.54***	21.22***	22.41***
	(0.000)	(0.000)	(0.000)
Observations	331	331	331
Number of subjects	45	45	45

Linear model with clustered s.e., p-value in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Table S7. Linear regressions with the dependent variable equal to the peak pupil dilation (in % change from baseline) on the feedback screen. The variable *Prediction Error* is equal to the absolute difference between the chosen number and the target number. *Post-Commit* is equal to 1 for trials after the commitment, and *Commit* $>$ *0* and *Commit-to-0* are dummy variables for subjects who committed to a number greater than 0 or committed to 0. The model included clustered standard errors to account for repeated observations per subject.

	(1)	(2)
	Peak Pupil Dilation in % Change	
Prediction Error	2.441***	1.317*
	(0.001)	(0.056)
Commit $>$ 0 $\times$ Prediction Error	-1.124	
	(0.242)	
Post-Commit $\times$ Prediction Error	-4.219***	-1.921***
	(0.000)	(0.001)
Commit $>$ 0 $\times$ Post-Commit $\times$ Prediction Error	2.298**	
	(0.015)	
Commit-to-0 $\times$ Prediction Error		1.124
		(0.242)
Commit-to-0 $\times$ Post-Commit $\times$ Prediction Error		-2.298**
		(0.015)
Constant	13.76***	13.76***
	(0.000)	(0.000)
Observations	1340	1340
Number of subjects	47	47

Linear model with clustered s.e., p-value in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Table S8. Estimation Results: EL v.s RL.

Subject	Commit	Commit	Negative log-likelihood		EL parameters			RL parameters		
id	trial	number	EL	RL	d	q_1	q_2	λ	ϕ	$A_1(0)$
1	2	4	0.00	0.00	0.11	0.00	0.00	12.15	0.81	57.61
2	2	10	0.00	0.00	0.11	0.00	0.00	12.54	0.93	29.61
3	25	0	8.66	9.61	0.08	0.38	1.00	0.09	0.99	13.86
4	7	0	2.77	1.16	0.50	0.50	1.00	40.00	0.29	0.14
5	5	0	1.91	3.01	1.00	0.67	1.00	0.06	1.00	-30.12
6	6	0	0.00	1.18	0.33	0.00	1.00	40.00	0.31	0.43
7	–	–	0.00	0.00	1.00	0.00	0.00	12.35	0.86	55.73
8	11	1	1.91	3.13	0.33	0.33	0.00	0.10	1.00	21.29
9	2	7	0.00	0.00	0.11	0.00	0.00	12.54	0.93	29.61
10	22	0	0.00	2.30	0.08	0.00	1.00	40.00	0.52	60.00
11	8	0	4.50	4.97	0.17	0.25	1.00	0.17	0.73	26.07
12	6	3	0.00	0.00	1.00	0.00	0.00	22.78	0.85	43.44
13	4	0	1.91	2.78	1.00	0.33	1.00	0.71	0.23	4.20
14	7	7	0.00	0.00	0.14	0.00	0.00	18.10	0.87	49.57
15	5	0	0.00	1.64	1.00	0.00	1.00	40.00	0.10	0.07
16	4	0	0.00	1.81	0.33	0.00	1.00	40.00	0.21	1.04
17	30	0	2.50	4.83	0.20	0.20	1.00	0.28	1.00	4.32
18	11	0	0.00	3.70	0.25	0.00	1.00	40.00	0.10	60.00
19	10	0	4.77	5.22	0.11	0.22	1.00	0.20	0.82	20.13
20	18	0	3.92	5.10	0.13	0.00	0.95	0.14	0.79	60.00
21	16	0	0.00	1.97	0.13	0.00	1.00	40.00	0.34	60.00
22	12	0	0.00	1.06	0.33	0.00	1.00	40.00	0.20	1.25
23	–	–	10.36	13.01	0.08	0.47	1.00	0.03	1.00	23.16
24	–	–	3.25	5.07	0.17	0.10	1.00	0.21	0.66	60.00
25	–	–	3.80	5.44	0.14	0.00	0.94	0.16	0.76	60.00
26	5	0	0.00	1.81	1.00	0.00	1.00	40.00	0.21	0.04
27	–	–	0.00	3.85	0.10	0.00	1.00	2.55	0.49	60.00
28	5	7	0.00	0.00	0.14	0.00	0.00	20.06	0.83	57.28
29	–	–	16.83	18.56	0.20	0.00	0.60	0.07	0.51	60.00
30	5	2	0.00	0.00	1.00	0.00	0.00	26.09	0.69	27.20
31	–	–	15.28	17.70	1.00	0.00	0.67	0.04	0.44	60.00
32	6	4	0.00	0.00	1.00	0.00	0.00	18.31	0.84	50.90
33	6	7	0.00	0.00	0.11	0.00	0.00	20.03	0.87	49.78
34	–	–	7.51	8.37	0.17	0.13	0.75	0.06	0.78	60.00
35	3	6	0.00	0.00	0.11	0.00	0.00	21.88	0.85	38.64
36	12	0	5.73	5.70	0.11	0.33	1.00	0.14	0.81	23.38
37	17	0	3.97	4.98	0.14	0.00	0.95	0.24	0.69	60.00
38	5	0	0.00	0.92	0.50	0.00	1.00	40.00	0.10	0.67
39	6	0	0.00	0.92	0.33	0.00	1.00	40.00	0.10	7.35
40	28	0	0.00	1.08	0.17	0.00	1.00	40.00	0.23	60.00
41	–	–	12.22	14.29	0.25	0.00	0.30	0.02	0.97	60.00
42	2	4	0.00	0.00	0.11	0.00	0.00	20.91	0.88	11.36
43	11	0	0.00	1.08	0.17	0.00	1.00	40.00	0.23	60.00
44	5	8	0.00	0.00	0.50	0.00	0.00	16.72	0.90	30.55
45	19	2	3.35	4.41	0.20	0.09	0.00	0.04	1.00	60.00
46	9	1	3.01	4.14	0.17	0.13	0.00	0.05	1.00	48.69
47	2	6	0.00	0.00	0.11	0.00	0.00	12.54	0.93	29.61
48	–	–	3.35	6.81	0.14	0.00	0.91	0.10	0.74	60.00
49	16	0	0.00	1.00	0.20	0.00	1.00	40.00	0.17	60.00
50	9	2	0.00	0.00	0.20	0.00	0.00	18.02	0.78	10.03
51	14	2	6.11	9.66	0.10	0.30	0.00	0.04	1.00	60.00
52	–	–	8.15	8.51	0.25	0.00	0.42	0.16	0.61	60.00
53	2	4	0.00	0.00	1.00	0.00	0.00	18.28	0.81	52.12
54	11	0	4.50	6.28	0.13	0.25	1.00	0.10	0.95	16.72
55	2	5	0.00	0.00	0.11	0.00	0.00	12.54	0.93	29.61
56	–	–	9.41	10.23	0.50	0.17	0.91	0.11	0.61	60.00
57	20	5	5.58	7.65	0.09	0.15	0.00	0.04	1.00	60.00
58	7	6	0.00	0.00	0.20	0.00	0.00	25.80	0.85	35.72
59	13	0	5.00	7.87	0.10	0.20	1.00	0.12	1.00	16.41