Supporting Information 1 • S1 Figure. Participant behaviour in the pilot experiment. 2 • **S1** Text. Preregistration description. 3 • S1 Table. Overview of analyses in the pre-registration (PR) and the paper. 4 • S2 Figure. Effect of additional parameters on the slowness prior effect. 5 • S2 Text. Effect sizes and confidence intervals for the mixed effects models. - S2 Table. Best model predicting predicting cumulative reward in the learning phase. 7 - S3 Table. Best model predicting correct choices in the learning phase 8 - **S4 Table**. Mixed effects model predicting participant learning phase choices from the 9 feature positions in the slow blocks. 10 - **S5** Table. Mixed effects model predicting participant learning phase choices from the 11 feature positions in the fast blocks. 12 - S6 Table. Best model predicting correct choices in the test phase. 13 - S7 Table. Best model predicting choices from the reward difference in the test phase. 14 • S3 Figure. Models fit individual participant learning curves. 15 • S4 Figure. Model performance in the slow and fast condition. 16 • **S5 Figure**. Development of the learning rates of the four learning rate model. 17 • **S6 Figure**. Parameter and model recovery. 18



Figure S1: **Participant behaviour in the pilot experiment.** a) Accuracy increased from 51% in the first ten trials to 67% in the last ten trials of the learning phase (t(49) = 8.35, p < .001, d = 1.18). Note that here the learning phase was capped at 45 trials, explaining the lower accuracy compared to the main experiment. b) We also found a decrease in exploratory 'accept' choices throughout learning, from around 84% to 64% (t(49) = -9.688, p < .001, d = 1.394). c) Similar to the main experiment, participants start selectively rejecting low value stimuli in the learning phase. d) Participants were able to correctly identify higher value stimuli from previously unseen stimuli in the test phase (mean accuracy 71% significantly higher than chance t(49) = 12.26, p < .001, d = 5.79). e) Participants accumulated marginally more reward in slow than in fast blocks in the learning phase $(t(49) = 1.57, p_{1-sided} = .061, d = 0.22)$. f) Participants increase in cumulative reward in the learning phase was numerically higher in slow than in fast blocks ($\beta = 25.16, 95\%$ CI = [-6.52 to 56.83], $X^2(1) = 2.37$, p = .124). g) We did not find a difference in test phase accuracy between slow and fast blocks. Grey points and lines indicate individual participants $(t(49) = 1.14 p_{1-sided} = .130, d = 0.16)$.

¹⁹ S1 Preregistration description

The main behavioural predictions and analyses followed a preregistered plan submitted prior to data collection (see https://osf.io/6dy8f and S1 Table below). ANOVAs were replaced with mixed effects models as these have been shown to better take into account individual differences between participants [73, 75, 76]. Two analyses were added to investigate the main effects in more detail, see S1 Table.

While the task and conditions are identical between the pre-registration and the paper (learning phase and test phase, bi-dimensional stimuli with slow/fast and relevant/irrelevant feature), the design in the pre-registration differs in three key ways: (a) multiple levels of slow feature variability, (b) fast feature variability determined by a Gaussian random walk instead of random sampling, and (c) the parameters of the colour space used. We based these changes on pilot data included in the data

- ²⁹ repository, but not analysed here.
- The pre-registration lists mean accuracy below 65% as an exclusion criterion, however during data collection it became clear that this criterion was too stringent, as it would entail excluding criterion was not applied, instead, no participants were excluded. The main results remained unchanged when applying this exclusion criterion. In the main experiment, the comparison of learning phase
- cumulative reward was marginal ($M_S = 351.85 \pm 15.53$, $M_F = 319.13 \pm 19.35$, t(29) = 1.69, $p_{1-sided} =$
- $_{36}$.051, d = 0.31), however the effect in test phase accuracy was stronger than with the full sample
- $M_S = 83\% \pm 1, M_F = 80\% \pm 1, t(29) = 2.08, p_{1-sided} = .023, d = 0.38)$. In the pilot experiment, we
- $_{38}$ did not find evidence for the effect, however note that after exclusion N=17 (learning phase cumulative
- reward: $M_S = 224.43 \pm 15.57$, $M_F = 214.49 \pm 21.30$, t(16) = 0.53, $p_{1-sided} = .302$, d = 0.13; test phase
- 40 accuracy $(M_S = 85\% \pm 2, M_F = 82\% \pm 2, t(16) = 1.14, p_{1-sided} = .135, d = 0.28).$

Main Analyses	PR	Paper	Comment
One-sided paired t-test comparing learn-	ves	ves	
ing phase reward in slow vs fast blocks	900	<i>y</i> co	
One-sided paired t-test comparing learn-	ves	ves	
ing phase accuracy in slow vs fast blocks	5.00	5	
One-sided paired t-test comparing test	ves	ves	
phase accuracy in slow vs fast blocks		5	
Additional Analyses	PR	Paper	Comment
Two-way repeated measures ANOVA: ef-	yes	S2a	replaced with: Linear mixed effects
fect of within-subject factor condition		Fig	model with trial number, condition
(slow vs. fast) and within-subject factor		_	(slow/fast), and trial×condition interac-
time (early vs. late half of the block) on			tion as predictors, predicting learning
learning phase reward			phase trial-wise cumulative reward
Two-way repeated measures ANOVA: ef-	yes	S2b	replaced with: logistic mixed effects
fect of within-subject factor condition		Fig	model with trial number, stimulus value,
(slow vs. fast) and within-subject factor			condition $(slow/fast)$ and $trial \times value$
time (early vs. late half of the block) on			as predictors, predicting learning phase
learning phase accuracy			choice accuracy
Linear mixed effects model with the ab-	no	yes	
solute value difference between the shown			
stimuli and condition (slow vs. fast) as			
predictors, predicting choice accuracy in			
the test phase			
Linear mixed effects model with relevant	no	yes	
and irrelevant feature angles as (circu-			
lar) predictors, predicting learning phase			
choices			
Two-way repeated measures ANOVA: ef-	yes	S2d-t	
fect of within-subject factor condition		Fig	
(slow vs. fast) and within-subject fac-			
tor relevant leature (colour vs. snape) on			
learning phase reward/accuracy and test			
Descrete completion between learning		C 22	
Pearson correlation between learning	yes	52C Fig	
phase accuracy of reward and test phase		гıg	
Two way mixed model ANOVA: affect	TIOC	no	The experiment design no longer in
of within subject factor condition (slow	yes	по	aluded different levels for the slow speed
vs fast) and between subject factor slow			cluded different levels for the slow speed.
speed (random walk sd 30.45 or 60) on			
learning phase reward/accuracy and test			
phase accuracy			
accuracy Two-way mixed model ANOVA: effect of within-subject factor condition (slow vs. fast) and between-subject factor slow speed (random walk sd 30,45 or 60) on learning phase reward/accuracy and test phase accuracy	yes	no	The experiment design no longer in- cluded different levels for the slow speed.

Table S1: Overview of analyses in the pre-registration (PR) and the paper.



Figure S2: Effect of additional parameters on the slowness prior effect. a) We compared the behavioural effect of feature speed on accumulated reward in the first and second half of each learning phase. We did not find a significant interaction between feature speed and block half (F(1, 49) = 0.48,p > .05). We did find significant main effects of feature speed (F(1, 49) = 4.70, p = .035) and block half (F(1, 49) = 191, p < .001). b) We found equivalent results using learning phase accuracy as our dependent measure (interaction: F(1, 49) = 0.32, p = 0.574, feature speed: F(1, 49) = 3.90, p = 0.054, block half: F(1,49) = 177, p < .001). c) There was a large correlation between accumulated reward in the learning phase and accuracy in the test phase (r = .86, p < .001). d) We examined the effect of feature type (colour/shape) on the effect of feature speed. We did not find a significant interaction between feature speed and feature identity on accumulated reward in the learning phase (F(1, 49) = 0.019, p > .05), though the main effects of feature speed (F(1, 49) = 4.70, p = 0.035)and feature identity were significant (F(1,49) = 23.22, p < .001). e) Results were similar when using learning phase accuracy as the dependent measure (interaction: F(1, 49) = 0.09, p = 0.764, speed: F(1,49) = 3.89, p = 0.054, type: F(1,49) = 17.5, p < .001). f) We found a significant interaction between feature speed and feature identity in the test phase accuracy (F(1, 49) = 4.614, p = 0.0367). Participants were significantly more accurate on slow compared to fast blocks when colour was the relevant feature (p = 0.014), but not when the shape was the relevant feature (0.451). The main effect of feature speed (F(1, 49) = 3.417, p = 0.071) was marginal, while the main effect of feature identity (F(1,49) = 39.05, p < 0.001) was significant. Grey points and lines are individual participants. All data is from the main experiment.

41 S2 Effect sizes and confidence intervals for the mixed effects 42 models

⁴³ The following tables report the parameter estimates for the mixed effect models. CI_l and CI_u denote ⁴⁴ the lower and upper bound of the 95% confidence interval, respectively. The standard deviation of the ⁴⁵ random effects is reported under σ_{rand} . Not all fixed effects are included as random effects. For all

⁴⁶ models, random effects are per subject.

Parameter	Estimate	CI_l	CI_u	$\sigma_{\rm rand}$
(Intercept)	-124.03	-146.25	-101.81	75.41
condition [slow]	-17.17	-36.90	2.57	59.92
trial	254.27	203.32	305.22	180.64
condition \times trial	39.07	2.44	75.70	123.05
Residual				114.76

Table S2: Best model predicting predicting cumulative reward in the learning phase.

Parameter	Estimate	CI_l	CI_u	$\sigma_{ m rand}$
(Intercept)	-0.63	-0.79	-0.48	0.41
condition [slow]	0.08	-0.00	0.16	0.21
$ R_t - 50 $	-0.23	-0.33	-0.13	
trial	1.60	1.48	1.73	
$ R_t - 50 \times \text{trial}$	0.53	0.41	0.66	

Table S3: Best model predicting correct choices in the learning phase.

Parameter	Estimate	CI_l	CI_u	χ^2	Df	$\Pr(>Chisq)$	$\sigma_{\rm rand}$
(Intercept)	3.18	2.92	3.45				0.59
$cos(heta_R)$	-1.00	-1.39	-0.62	110.98	1	< .001	0.85
$sin(heta_R)$	-0.07	-0.36	0.23	0.14	1	0.7116	
$cos(heta_I)$	-0.04	-0.34	0.26	2.75	1	0.0970	0.18
$sin(heta_I)$	0.02	-0.28	0.31	0.24	1	0.6220	
trial	-2.63	-2.89	-2.38	423.41	1	< .001	
$cos(\theta_R) \times trial$	2.97	2.60	3.34	247.04	1	< .001	
$sin(\theta_R) \times trial$	0.07	-0.28	0.43	0.15	1	0.6943	
$cos(\theta_I) \times trial$	-0.04	-0.40	0.32	0.04	1	0.8407	
$sin(\theta_I) \times trial$	-0.00	-0.36	0.36	0.00	1	0.9860	

Table S4: Mixed effects model predicting participant learning phase choices from the feature positions in the slow blocks. The statistical tests reported are Type-II Wald χ^2 tests.

Parameter	Estimate	CI_l	CI_u	χ^2	Df	Pr(>Chisq)	$\sigma_{\rm rand}$
(Intercept)	3.02	2.75	3.29				0.63
$cos(heta_R)$	-1.28	-1.65	-0.92	96.04	1	< .001	0.81
$sin(heta_R)$	-0.21	-0.50	0.08	0.22	1	0.6367	
$cos(heta_I)$	-0.18	-0.47	0.12	7.07	1	0.0078	0.12
$sin(heta_I)$	-0.12	-0.41	0.17	0.00	1	0.9629	
trial	-2.37	-2.62	-2.12	306.90	1	< .001	
$cos(\theta_R) \times trial$	3.13	2.78	3.49	297.79	1	< .001	
$sin(\theta_R) \times trial$	0.24	-0.11	0.59	1.87	1	0.1712	
$cos(\theta_I) \times trial$	0.09	-0.26	0.44	0.26	1	0.6095	
$sin(\theta_I) \times trial$	0.15	-0.21	0.50	0.66	1	0.4166	

Table S5: Mixed effects model predicting participant learning phase choices from the feature positions in the fast blocks. The statistical tests reported are Type-II Wald χ^2 tests.

Parameter	Estimate	CI_l	CI_u	$\sigma_{ m rand}$
(Intercept)	1.16	0.99	1.33	0.57
condition [slow]	0.14	0.01	0.28	0.40
$ R_{\mathrm{diff},t} $	0.46	0.42	0.51	

Table S6: Best model predicting correct choices in the test phase.

Parameter	Estimate	CI_l	CI_u	$\sigma_{ m rand}$
(Intercept)	0.06	-0.02	0.13	0.20
condition [slow]	-0.04	-0.12	0.04	0.10
$R_{\mathrm{diff},t}$	1.19	1.13	1.25	
condition [slow] $\times R_{\text{diff},t}$	0.13	0.04	0.21	

Table S7: Best model predicting choices from the reward difference in the test phase.



Figure S3: Models fit individual participant learning curves. Participant learning curves overlaid with the model learning curves, simulated using the parameter values obtained from maximum likelihood fitting.



Figure S4: Model performance in the slow and fast condition. Cumulative reward relative to chance level obtained in the learning phase by the models using **a**) reward maximising parameters and **b**) maximum likelihood parameters.

47 S3 Development of learning rates



Figure S5: **Development of the learning rates of the four learning rate model.** Plots show the development of the learning rates across the trials of the learning phase. The learning rates on the first trial were obtained through maximum likelihood fitting. With decreasing uncertainty about the stimulus values, the learning rates decreased. The learning rates could not increase. Each line is an individual participant, averaged across blocks.



Figure S6: **Parameter and model recovery.** Model fitting and comparison was performed as described in the Methods. 100 data-sets were simulated for each model using random parameter values. Dot plots show the relationship between the true learning rate and the learning rate obtained through maximum likelihood fitting. Distributions of both are shown in grey. Points are individual simulations. The matrix shows model recovery. True models are accurately identified in most simulations. The 4LR model is sometimes misidentified as the $2LR_c$ and to a lesser extent the $2LR_f$ model. This likely is because the 4LR model is a specialised case of these two models. If the four learning rates of the 4LR model are similar to each other, this model behaves similarly to the two-learning (2LR) rate models.