MCRL Experiment with control conditions

Results

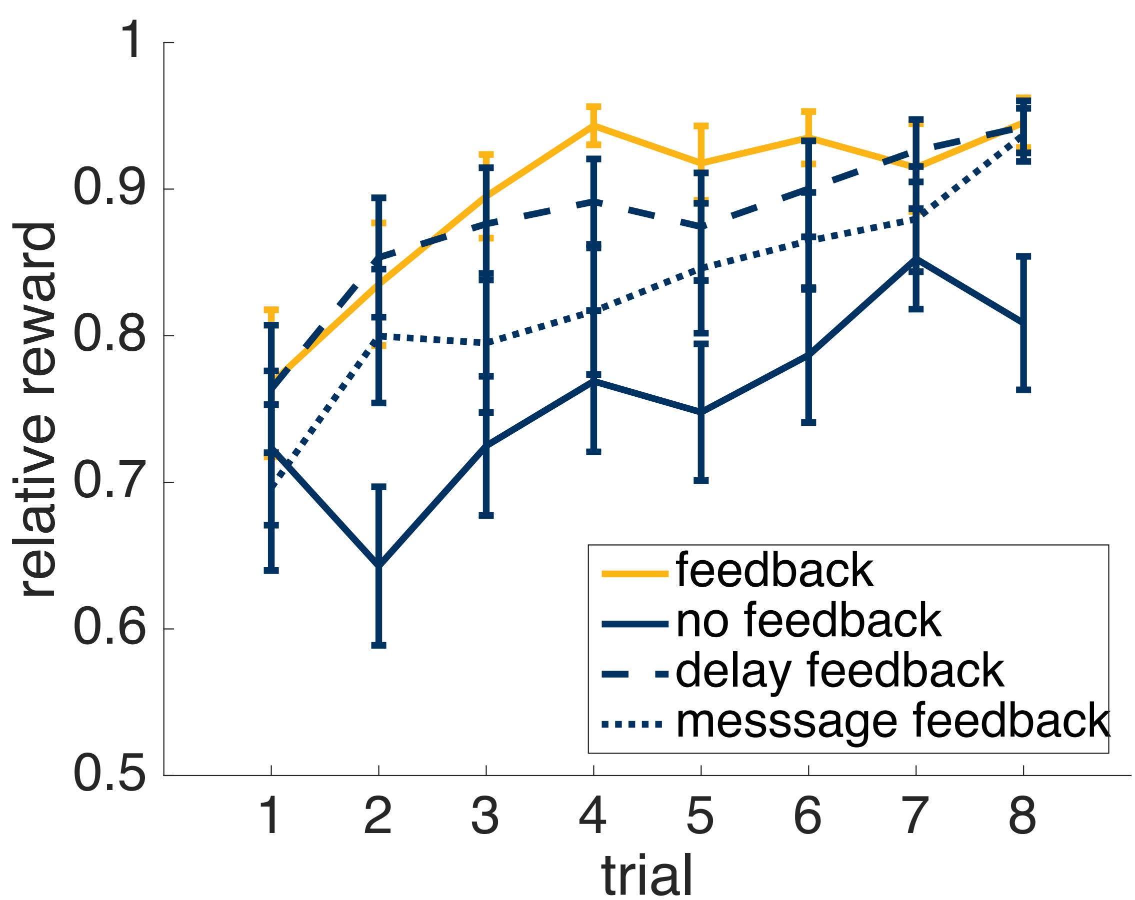
We modeled the learning curves of each dependent variable $Y_i(t)$ as a function of the trial number t, the presence of feedback delays $D \in \{0,1\}$, and the presentation of feedback messages $M \in \{0,1\}$ according to

$$Y_i(t) = (1 - \beta_0) \cdot \text{sigmoid}\big(\beta_1 + \text{t} \cdot (\beta_2 + \beta_3 \cdot D + \beta_4 \cdot M + \beta_5 \cdot D \cdot M)\big),$$

where β_0 determines the learner's asymptotic performance, β_1 determines the initial performance, β_2 is the learning rate without feedback, β_3 and β_4 measure the acceleration of learning by the addition of feedback delays and feedback messages respectively, and β_5 quantifies their potential interaction.

To determine which of the feedback variables contribute to the learning rate, we performed quantitative model comparisons using the Bayesian Information Criterion (BIC).

Relative Reward



The learning curve for the relative reward obtained by our participants was best explained by the model including both feedback variables but not their interaction (BIC 277.2). According to the BIC, the full model (BIC 283.4) and the restricted models that excluded one or both of the feedback factors (BIC >285.7) explained the data significantly less well.

As Table 1 shows, all coefficients of the winning model were significantly larger than zero. Most importantly, the addition of feedback delays increased the learning rate by 0.45 ± 0.14 and the addition of feedback messages increased it by 0.17 ± 0.06. The absence of the interaction term in the winning model suggests that the contributions of these two feedback mechanisms increased the learning rate independently of one another. Furthermore, an F-test revealed that the difference between the effects of the delays and the messages was statistically significant ($F(1{,}1459) = 7.41, p = 0.0066$). This supports the conclusion that the delays were more effective at accelerating metacognitive learning than the messages.

Table 1: Nonlinear Regression of Relative Reward on Trial Number according to the best model

	Estimate	SE	t	p value
β_0	0.0680	0.016872	4.0335	5.7791e-05
β_1	0.8560	0.13727	6.2357	5.8758e-10
β_2	0.1441	0.040606	3.5494	0.00039834
β_3	0.4539	0.13642	3.3269	0.00090016
β_4	0.1682	0.057432	2.9279	0.0034654

Number of observations: 1464, Error degrees of freedom: 1459
Root Mean Squared Error: 0.264
R-Squared: 0.0779, Adjusted R-Squared 0.0754
F-statistic vs. zero model: 2.99e+03, p-value = 0

Optimal Routes

The learning curves of the frequency with which participants found the optimal route were best explained by the model that included both feedback regressors but not their interaction (BIC 1658.9). The BIC of the full model (BIC 1664) and the BICs of the reduced models without one or both of the feedback regressors were larger (all BICs ≥ 1659.5).

As shown in

Table 2, all regression coefficients were statistically significant. Most importantly, feedback delays accelerated learning by 0.40 ± 0.14 and feedback messages accelerated it by 0.14 ± 0.06. Furthermore, an F-test revealed that the difference between the effects of the delays and the messages was statistically significant ($F(1{,}1459) = 6.88, p = 0.0088$). This supports the conclusion that the delays were more effective at accelerating metacognitive learning than the messages.

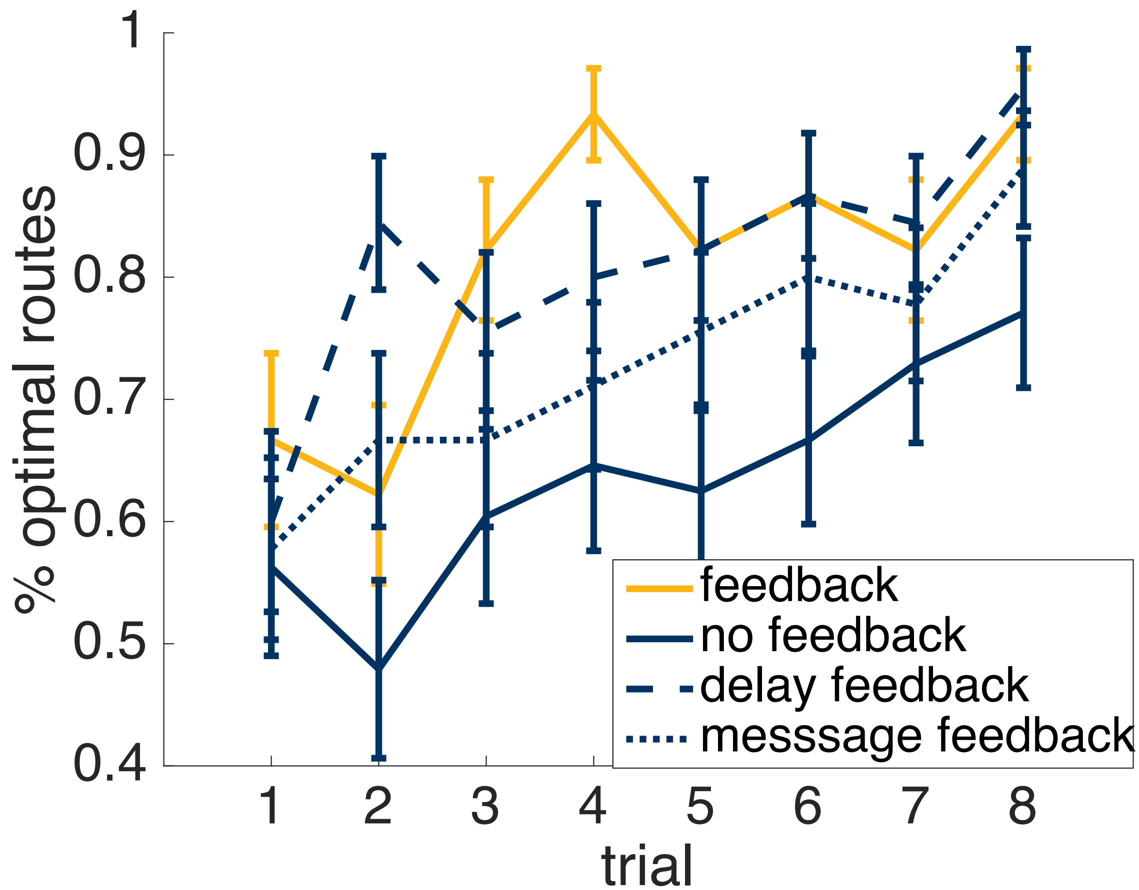


Figure 1: Learning curves for the frequency of finding the optimal route.

Table 2: Nonlinear regression of the frequency with which participants found the optimal route on trial number and feedback.

	Estimate	SE	t	p
β_0	0.1093	0.0303	3.6027	0.0003
β_1	0.2367	0.1686	1.4038	0.1606
β_2	0.1646	0.0500	3.2923	0.0010
β_3	0.4041	0.1359	2.9744	0.0030
β_4	0.1395	0.0593	2.354	0.0187

Number of observations: 1464, Error degrees of freedom: 1459
Root Mean Squared Error: 0.423
R-Squared: 0.0627, Adjusted R-Squared 0.0601
F-statistic vs. zero model: 930, p-value = 0

Number of Clicks

The learning curves of the number of clicks were best explained by the restricted model including both feedback regressors but not their interaction (BIC 8840.3). The BIC of the full model (BIC 8845.6) and the BICs of the reduced models without one or both of the feedback regressors were larger (all BICs ≥ 8844.1).

As shown in Table 3, the feedback delays ($\beta_3 = 0.652 \pm 0.1554$) and the feedback messages ($\beta_4 = 0.238 \pm 0.0660$) significantly accelerate learning to gather more information. Furthermore, an F-test revealed that the difference between the effects of the delays and the messages was statistically significant ($F(1,1459) = 10.04, p = 0.0016$). This again supports the conclusion that the delays were more effective at accelerating metacognitive learning than the messages.

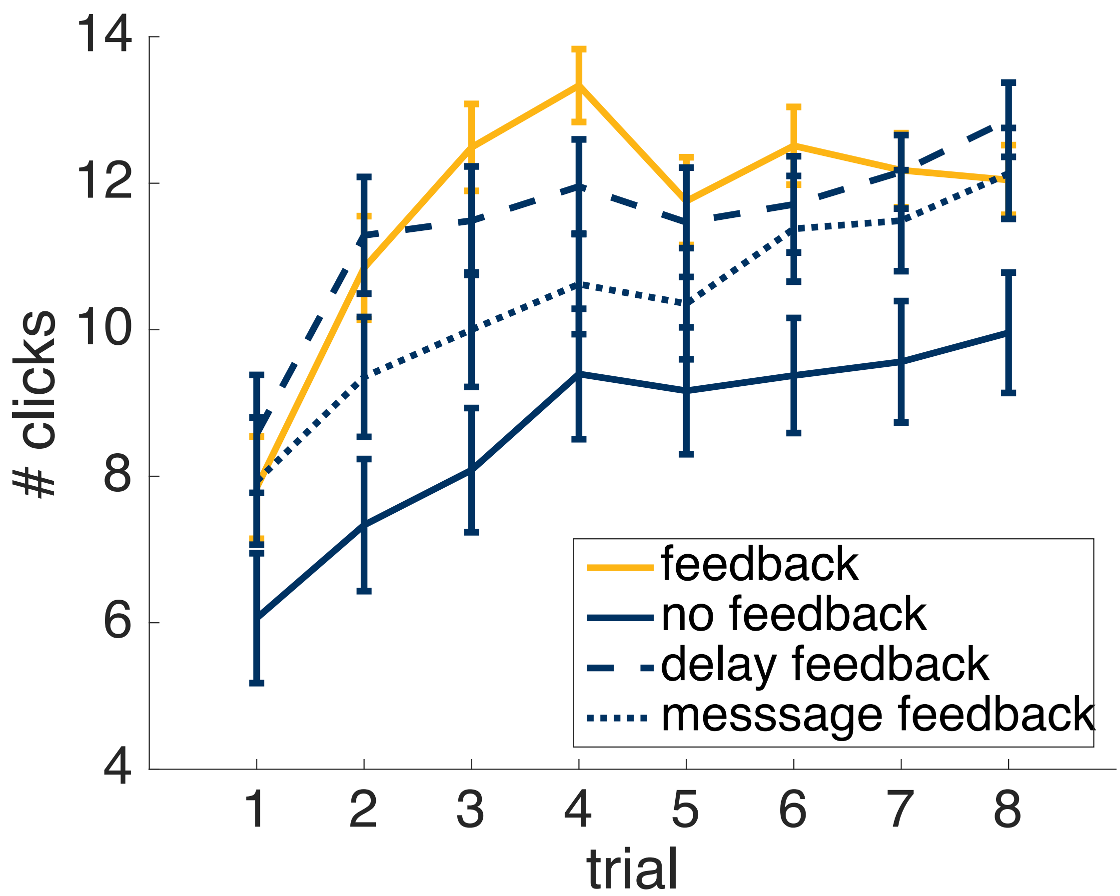


Figure 2: Learning curves for the number of clicks

Table 3: Nonlinear regression of the number of clicks on the trial number and feedback regressors.

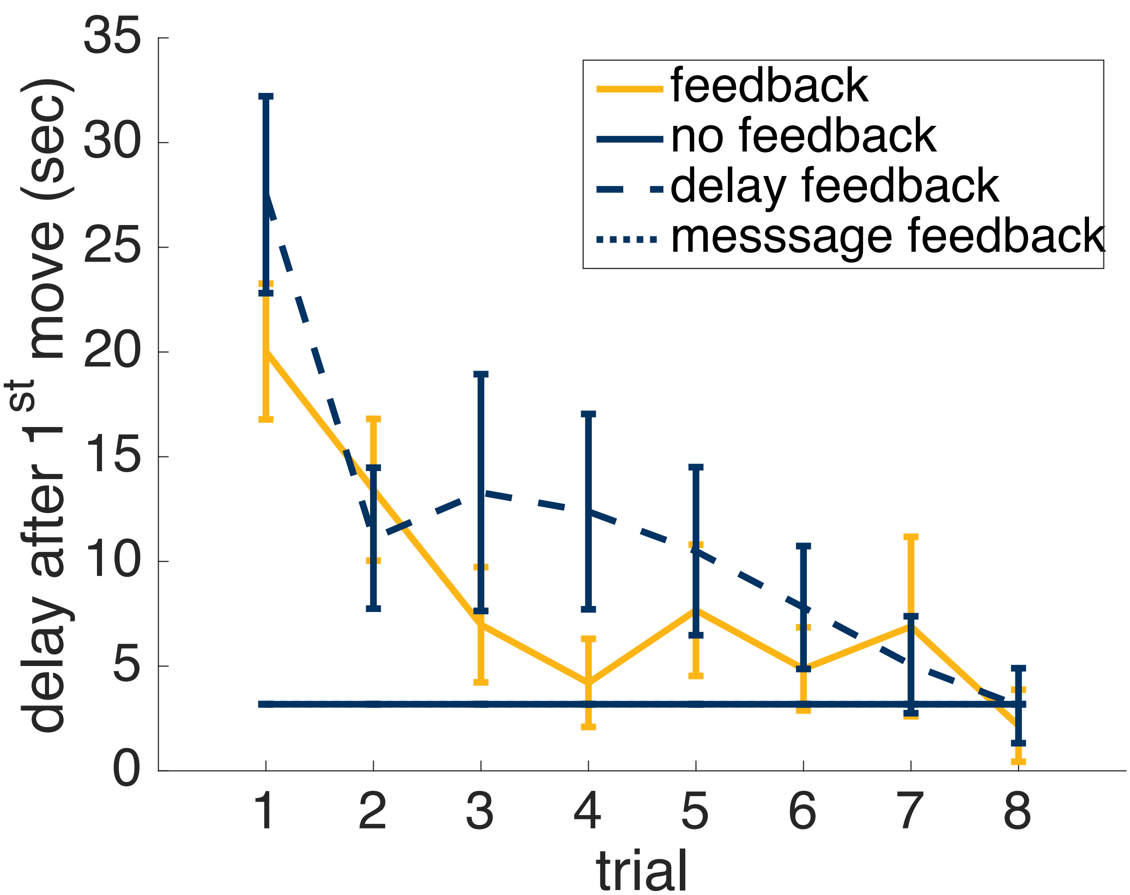
Estimated Coefficients:

	Estimate	SE	t	p

β_0	-11.293	0.25264	-44.698	1.3875e-275
β_1	-0.0011251	0.1538	-0.0073151	0.99416
β_2	0.20487	0.043051	4.7587	2.142e-06
β_3	0.65193	0.15545	4.1938	2.9085e-05
β_4	0.23802	0.066076	3.6022	0.00032618

Number of observations: 1464, Error degrees of freedom: 1459
Root Mean Squared Error: 4.91
R-Squared: 0.109, Adjusted R-Squared 0.106
F-statistic vs. zero model: 1.37e+03, p-value = 0

Delays



An ANOVA suggested that the average delay differed significantly between early versus late trials but the effect of experimental condition was not statistically significant (see Table 4). Yet, the average delays in the condition with full feedback (8.275 ± 1.1sec) and delay feedback

(11.34 ± 1.41sec) were higher than the constant delay in the conditions with no feedback or feedback messages only (3.18 sec).

Table 4: ANOVA of delays

Analysis of Variance

Source	Sum Sq.	d.f.	Mean Sq.	F	Prob>F
trial	12484.4	7	1783.49	6.38	0
condition	2004.9	3	668.3	2.39	0.0672
Error	406436.2	1453	279.72		
Total	420925.5	1463			

Constrained (Type III) sums of squares.