

Humans reconfigure target and distractor processing to address distinct task demands

Supplementary Materials

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Supplementary Tables

Target and distractor sensitivity (Attend-Motion)					
DV	Predictors	Exp 1 (df = 45) Effect size (<i>d</i>)	Exp 2 (df = 25) Effect size (<i>d</i>)	Exp 3 (df = 45) Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Target coherence		4.39	5.44	5.69×10⁻⁵³
	Distractor congruence	0.732	0.352	0.269	0.000916
	Target × Distractor		0.0522	0.145	0.6210
RT	Target coherence		-1.47	-1.63	2.71×10⁻²¹
	Distractor congruence	0.125	0.179	0.407	0.121
	Target × Distractor		0.0710	0.0371	0.864

Supplementary Table 1. Effect sizes are calculated from MAP group-level regression estimates. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Target and distractor sensitivity (Attend-Color - Attend-Motion)					
DV	Predictors	Exp 1 Effect size (<i>d</i>)	Exp 2 Effect size (<i>d</i>)	Exp 3 Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Target coherence		-0.588 (df = 50.0)	-0.615 (df = 89.8)	1.00×10⁻¹⁰
	Distractor congruence	0.432 (df = 88.9)	0.743 (df = 49.1)	0.971 (df = 75.8)	5.79×10⁻¹⁹
RT	Target coherence		0.00957 (df = 44.4)	0.339 (df = 69.8)	0.182
	Distractor congruence	-0.804 (df = 78.8)	-1.19 (df = 42.8)	-1.38 (df = 59.1)	2.69×10⁻³¹

Supplementary Table 2. Effect sizes are calculated from Welsh's contrasts across regression models. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Correlations between RT and accuracy betas			
Experiment	Correlands	MAP r-stat	<i>p</i> -value
Exp 1 (df = 54)	Distractor Betas	-0.891	1.95×10⁻²⁰
Exp 2 (df = 38)	Target Betas	-0.712	1.27×10⁻⁷
	Distractor Betas	-0.875	7.48×10⁻¹⁴
Exp 3 (df = 58)	Target Betas	-0.540	4.20×10⁻⁶
	Distractor Betas	-0.907	1.05×10⁻²³

Supplementary Table 3. Parameter correlations are calculated from the MAP group-level parameter covariance. Statistically significant *p*-values (two-tailed, $\alpha = 0.05$) are shown in bold.

Effects of previous conflict on feature sensitivity (Attend-Motion)					
DV	Predictors	Exp 1 (df = 41) Effect size (<i>d</i>)	Exp 2 (df = 19) Effect size (<i>d</i>)	Exp 3 (df = 39) Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Distractor × Prev Distract	0.0113	-0.176	0.293	0.578
	target × Prev Target		-0.00795	-0.424	0.268
RT	Distractor × Prev Distract	0.503	-0.427	0.181	0.291
	target × Prev Target		0.131	-0.0333	0.777

Supplementary Table 4. Effect sizes are calculated from MAP group-level regression estimates. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Effects of previous conflict on feature sensitivity (Attend-Color - Attend-Motion)					
DV	Predictors	Exp 1 Effect size (<i>d</i>)	Exp 2 Effect size (<i>d</i>)	Exp 3 Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Distractor-dependent (Distractor - Distractor)	0.505 (df = 52.7)	0.984 (df = 33.6)	0.280 (df = 47.7)	4.39×10⁻⁸
	Motion-dependent (Distractor - Target)		0.448 (df = 21.9)	0.651 (df = 40.2)	2.27×10⁻⁵
RT	Distractor-dependent (Distractor - distractor)	-0.629 (df = 80.2)	-0.956 (df = 29.3)	-1.20 (df = 70.7)	3.40×10⁻²³
	Motion-dependent (Distractor - Target)		-0.237 (df = 19.1)	-0.0929 (df = 39.3)	0.337

Supplementary Table 5. Effect sizes are calculated from Welch's contrasts across regression models. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Effects of incentives on feature sensitivity (Attend-Motion)			
DV	Predictors	Exp 3 (df = 41) Effect size (<i>d</i>)	<i>p</i> -value
Choice	Target × Reward	0.703	6.02×10⁻⁵
	Distractor × Reward	0.289	0.110
Lapse Rate	Reward	-0.0696	0.670
RT	Target × Reward	-0.126	0.415
	Distractor × Reward	-0.192	0.265
	Reward	-0.0955	0.516

Supplementary Table 6. Effect sizes are calculated from MAP group-level regression estimates. Statistically significant *p*-values (two-tailed, $\alpha = 0.05$) are shown in bold.

Effects of incentives on feature sensitivity (Attend-Color – Attend-Motion)			
DV	Predictors	Exp 3 Effect size (<i>d</i>)	<i>p</i> -value
Choice	Target × Reward	-0.279 (df = 59.0)	0.0363
	Distractor × Reward	-0.230 (df = 48.3)	0.117
RT	Target × Reward	0.0566 (df = 58.3)	0.667
	Distractor × Reward	0.271 (df = 77.0)	0.0199

Supplementary Table 7. Effect sizes are calculated from Welsh's contrasts across regression models. Statistically significant *p*-values (two-tailed, $\alpha = 0.05$) are shown in bold.

Dynamics of feature sensitivity across response times (Attend-Motion)					
DV	Predictors	Exp 1 (df = 38) Effect size (<i>d</i>)	Exp 2 (df = 21) Effect size (<i>d</i>)	Exp 3 (df = 41) Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Target × RT		2.03	1.31	3.30×10⁻²⁰
	Distractor × RT	-0.257	0.194	-0.490	0.0226
Lapse Rate	RT	0.509	0.763	-0.234	0.941
RT	Target × Accuracy		0.772	0.679	1.59×10⁻⁷
	Distractor × Accuracy	0.0758	-0.211	0.0199	0.931

Supplementary Table 8. Effect sizes are calculated from MAP group-level regression estimates. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Dynamics of feature sensitivity across response times (Attend-Color – Attend-Motion)					
DV	Predictors	Exp 1 Effect size (<i>d</i>)	Exp 2 Effect size (<i>d</i>)	Exp 3 Effect size (<i>d</i>)	Aggregate <i>p</i> -value
Choice	Target × RT		-2.08 (df = 23.0)	-1.09 (df = 46.1)	3.35×10⁻¹⁷
	Distractor × RT	-0.102 (df = 56.3)	-0.585 (df = 22.4)	-0.539 (df = 78.5)	4.57×10⁻⁵
RT	Target × Accuracy		-0.429 (df = 23.0)	-0.422 (df = 46.2)	0.00148
	Distractor × Accuracy	-0.344 (df = 66.4)	-0.648 (df = 29.6)	-0.723 (df = 78.6)	4.56×10⁻¹¹

Supplementary Table 9. Effect sizes are calculated from Welsh's contrasts across regression models. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Model Collinearity			
Model	Experiment	Accuracy Model Collinearity median [25% - 75%]	RT Model Collinearity median [25% - 75%]
Baseline	Experiment 1	1.4 [1.4 – 1.5]	1.1 [1.1 – 1.1]
	Experiment 2	1.4 [1.4 – 1.5]	1.1 [1.1 – 1.1]
	Experiment 3	1.4 [1.4 – 1.5]	1.1 [1.1 – 1.1]
Post-Conflict	Experiment 1	1.5 [1.4 – 1.5]	1.2 [1.1 – 1.3]
	Experiment 2	1.4 [1.4 – 1.5]	1.3 [1.2 – 1.3]
	Experiment 3	1.5 [1.4 – 1.5]	1.3 [1.2 – 1.3]
Reward	Experiment 3	1.4 [1.4 – 1.5]	1.2 [1.1 – 1.2]
Dynamics	Experiment 1	1.5 [1.5 – 1.6]	1.5 [1.3 – 2.0]
	Experiment 2	1.5 [1.4 – 1.5]	1.6 [1.4 – 1.7]
	Experiment 3	1.5 [1.4 – 1.5]	1.7 [1.5 – 2.0]
Post-Conflict Dynamics	Experiment 1	1.6 [1.6 – 1.8]	2.2 [1.7 – 3.3]
	Experiment 2	1.5 [1.4 – 1.5]	2.1 [1.8 – 2.4]
	Experiment 3	1.5 [1.5 – 1.6]	2.1 [1.7 – 2.5]
Reward Dynamics	Experiment 3	1.5 [1.5 – 1.6]	2.0 [1.7 – 2.4]

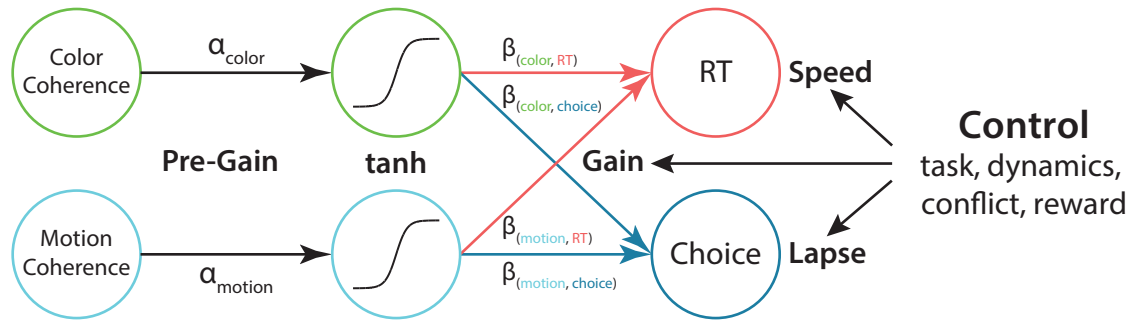
Supplementary Table 10. Belsley collinearity diagnostics for core models (from MATLAB’s collintest).

Diagnostic values are the ratio of the design matrix’s largest singular value to its smallest singular value, summarized at different participant quantiles (i.e., median is the participant at the 50th percentile). A value of 1 is perfect orthogonality, and values below 30 are within the default tolerance. All values are well below 30, indicating tolerable collinearity.

Across-block changes in Feature Sensitivity Dynamics				
DV	Predictors	Exp 2 Effect size (<i>d</i>)	Exp 3 Effect size (<i>d</i>)	Aggregate <i>p</i>-value
Choice	Block × Distractor × RT	-0.501	-0.644	5.21 × 10⁻⁶
	Block × Target × RT	0.348	0.480	.000576
	Block × Distractor	0.633	0.524	1.27 × 10⁻⁵
	Block × Target	0.0698	-0.0581	.501
Lapse Rate	Block	0.380	0.0793	.175
	Block × RT	-0.505	-0.277	.00342
RT	Block × Distractor × Accuracy	0.168	-0.397	.0399
	Block × Target × Accuracy	-0.142	-0.153	.286
	Block × Distractor	0.0498	-0.129	.215
	Block × Target	0.371	0.475	.000472
	Block × Accuracy	0.396	0.448	.000422
	Block	-0.970	-1.23	1.33 × 10⁻¹²

Supplementary Table 11. Effect sizes are calculated from Welsh's contrasts across regression models. *P*-values are aggregated across experiments, with statistically significant *p*-values (two-tailed, $\alpha = 0.05$) shown in bold.

Supplementary Figures



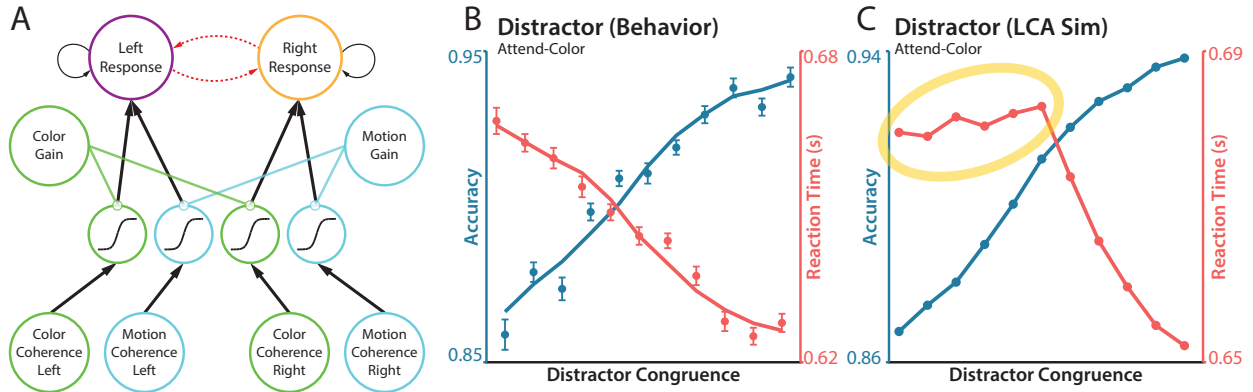
Supplementary Figure 1. Regression schematic. To estimate feature sensitivity, trial-specific color (green) and motion (cyan) coherence levels were passed through a hyperbolic tangent nonlinearity (tanh), with the α parameter determining the strength of the nonlinearity (see Methods). The linear relationships between transformed coherence and performance (RT in red and Choice in blue) were our estimates of participants' feature sensitivity. Our critical analyses tested whether potential indices of control (e.g., task instructions or incentives) moderated this feature sensitivity.



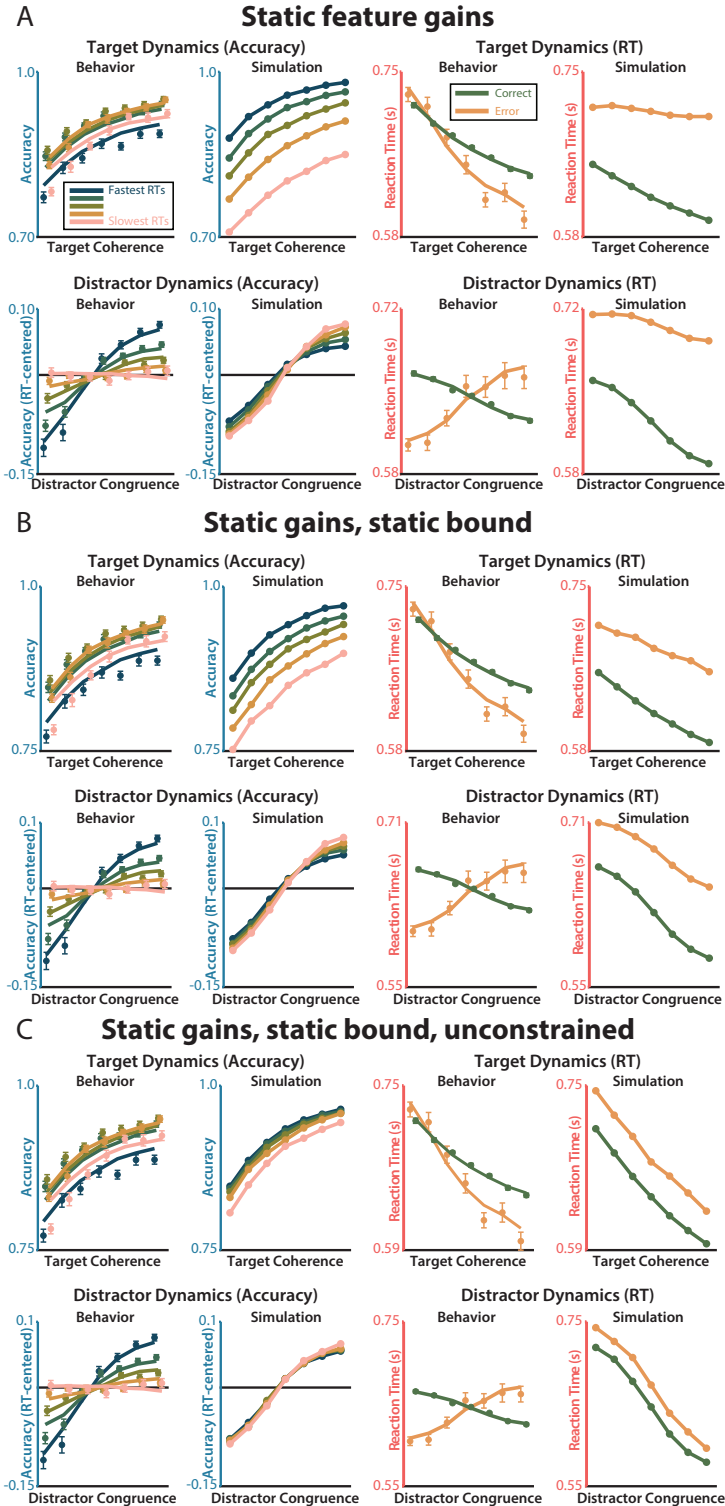
Supplementary Figure 2. Target-dependent adaptation. **A-B)** The relationship between target coherence and accuracy (A) was weaker when the previous trial had weaker target coherence (redder colors). There was not a significant effect for RT (B) Circles depict participant behavior and lines depict aggregated regression predictions.

C) Regression estimates for the current target coherence by previous target coherence interaction, within each experiment. **D-E)** There was not a significant relationship between distractor congruence and previous target coherence in accuracy (D) or RT (E). **F)** Regression estimates for the current distractor congruence by previous target coherence interaction, within each experiment. Error bars on behavior reflect within-participant SEM, error bars on regression coefficients reflect 95% CI.

Leaky Competing Accumulator (LCA)

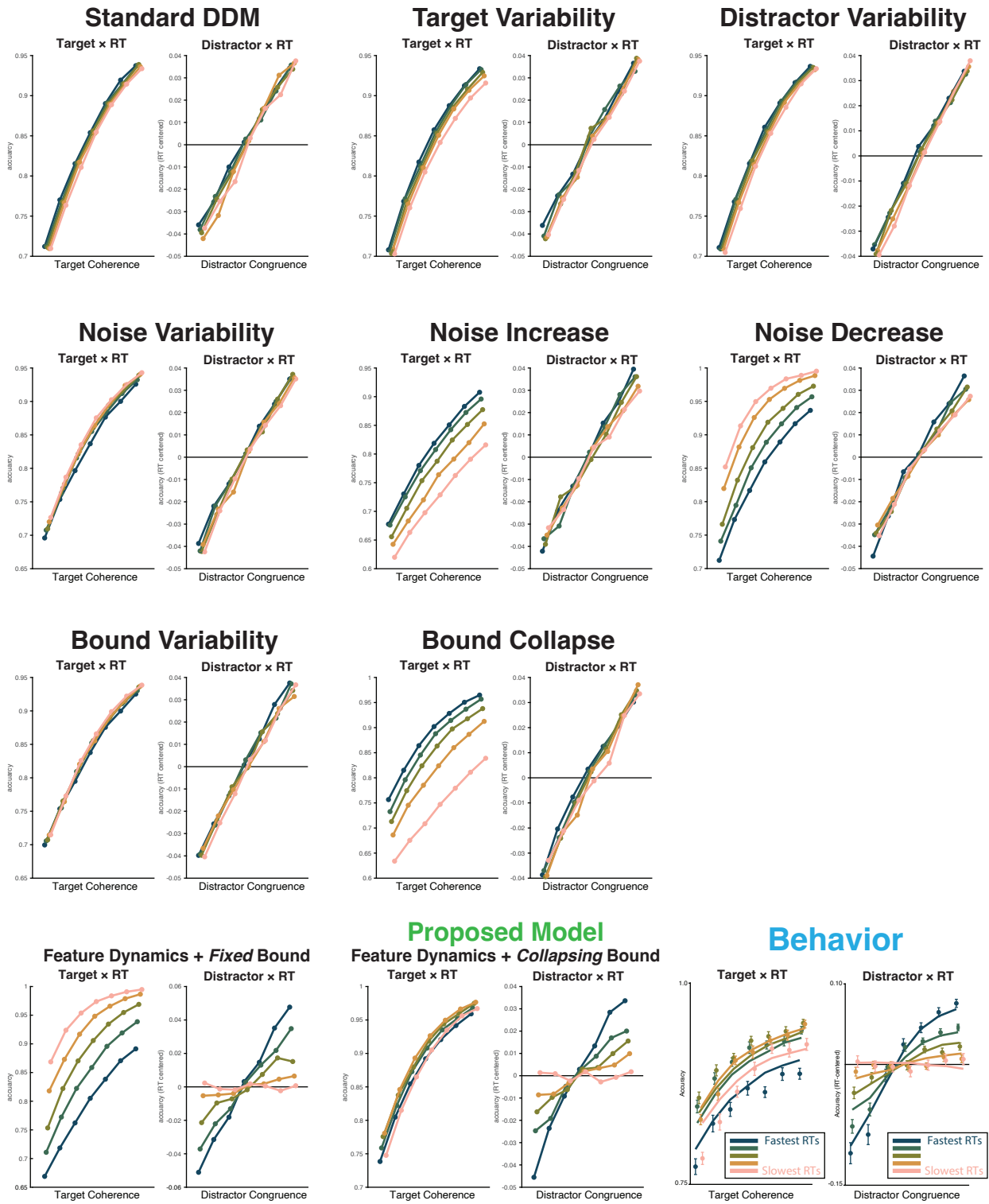


Supplementary Figure 3. Leaky competing accumulator simulation. **A)** We simulated behavior from a leaky competing accumulator (Usher and McClelland, 2001). In this model, the response accumulators directly compete. In our parameter regime, leak and competition parameters produce race-like accumulation dynamics (Bogacz et al., 2006; Weichart et al., 2020). **B-C)** We found that this parameter regime was unable to capture the effect of distractor congruence on reaction time, as stronger inputs (congruent or incongruent) produce faster RTs in a race-like regime (Teodorescu and Usher, 2013). Other parameter regime, producing DDM-like dynamics, would replicate our main simulation results (Bogacz et al., 2006).

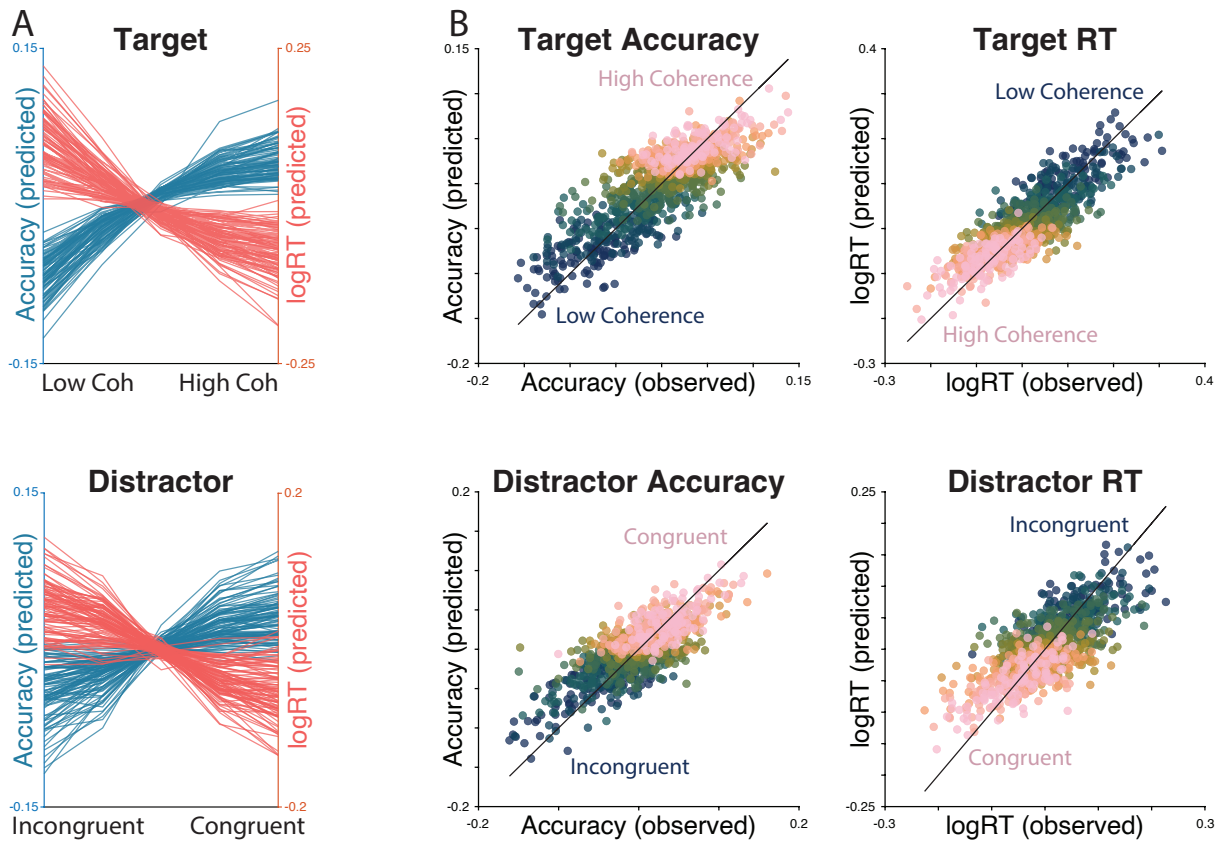


Supplementary Figure 4. Static feature gain simulations. We simulated the FFI model under different formulations that lack feature sensitivity dynamics, showing that gain dynamics are necessary to capture the RT- and Accuracy-dependent feature sensitivity we observed in participants' behavior. Feature-specific processes are necessary to capture the opposite-going dynamics on target sensitivity and distractor sensitivity. A) Static model without feature

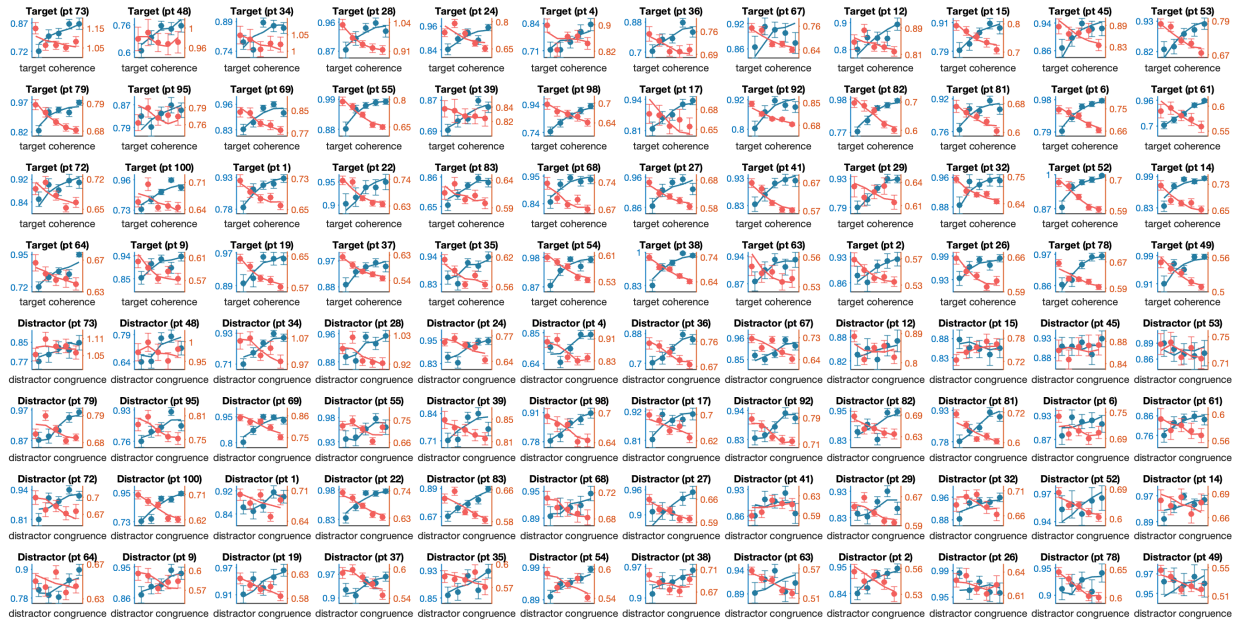
dynamics. B) Static model without feature dynamics or collapse response threshold. C) Static model without feature dynamics, collapsing response threshold, or positive-rectified accumulators.



Supplementary Figure 5. Dynamic drift diffusion simulations. Drift diffusion model (DDM) simulations demonstrating the predictions from alternative formulations of within- and across-trial dynamics. Data are simulated target and distractor psychometric curves, conditioned on simulated RT quintiles (1 million simulations per analysis). Row 1: Standard DDM, across-trial target gain variability, across-trial distractor gain variability. Row 2: across-trial accumulation noise variability, within-trial noise increase, within-trial noise decrease. Row 3: across-trial bound (threshold) variability, within-trial bound decrease ('collapsing bound'). Row 4: within-trial target gain enhancement and distractor suppression with fixed bound, within-trial target gain enhancement and distractor suppression with collapsing bound, participants' behavior. All simulations were performed using the dm package (package available at www.github.com/DrugowitschLab/dm; simulation scripts available at www.github.com/shenhavlab/PACT-public).

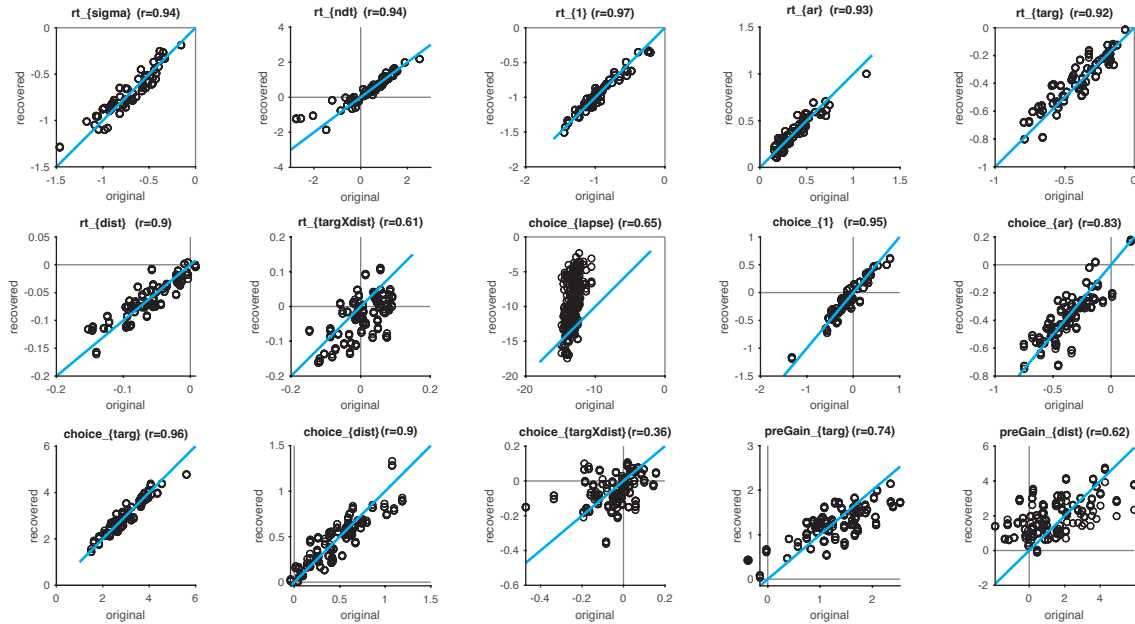


Supplementary Figure 6. Aggregated posterior predictive checks. **A)** Model predictions from participants in Experiments 2 and 3, showing predicted target sensitivity curves (top) and distractor sensitivity curves (bottom). Predictions are centered within-participant to remove individual intercepts. **B)** Model fit quality for participants in Experiments 2 and 3. Each participants' behavior (x-axis) is plotted against predicted behavior (y-axis), across five levels of target coherence (top) or distractor congruence (bottom; bluer to pinker indicates harder to easier conditions). Dots closer to the black identity reflect better model fit, and color gradients on y-axis reflect feature sensitivity. Predictions and behavior are centered within-participant to remove individual intercepts.

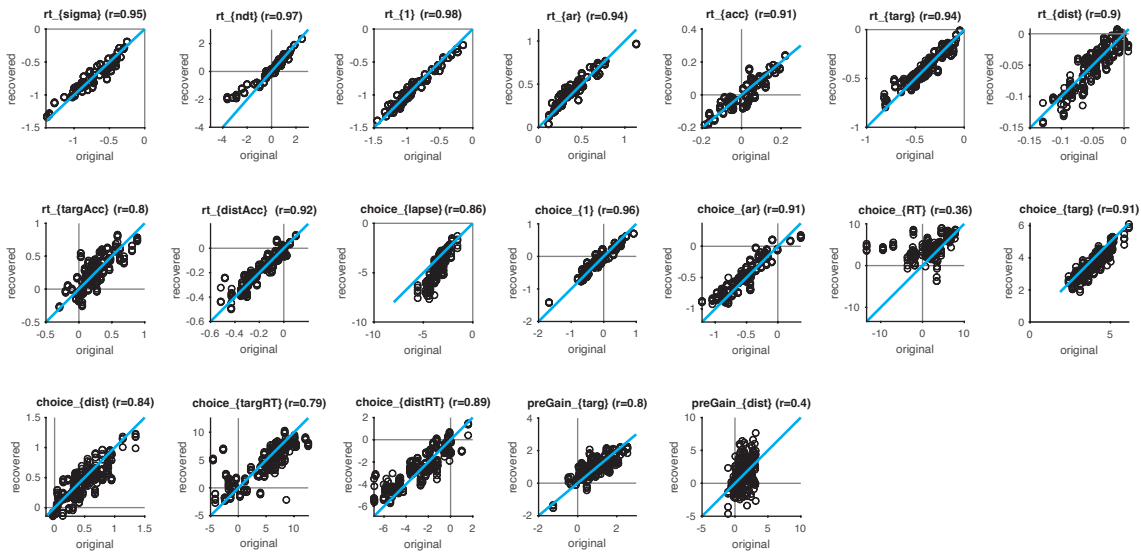


Supplementary Figure 7. Single-participant posterior predictive checks. Posterior predictive checks from 48 participants from Experiments 2 and 3, linearly spaced from the poorest model likelihood to the best model likelihood. First four rows are target sensitivity curves for accuracy (blue) and reaction time (red). Final four rows are distractor sensitivity curves (for the same participants) for accuracy (blue) and reaction time (red). Overlaid lines are single-trial model predictions aggregated like participants' behavior.

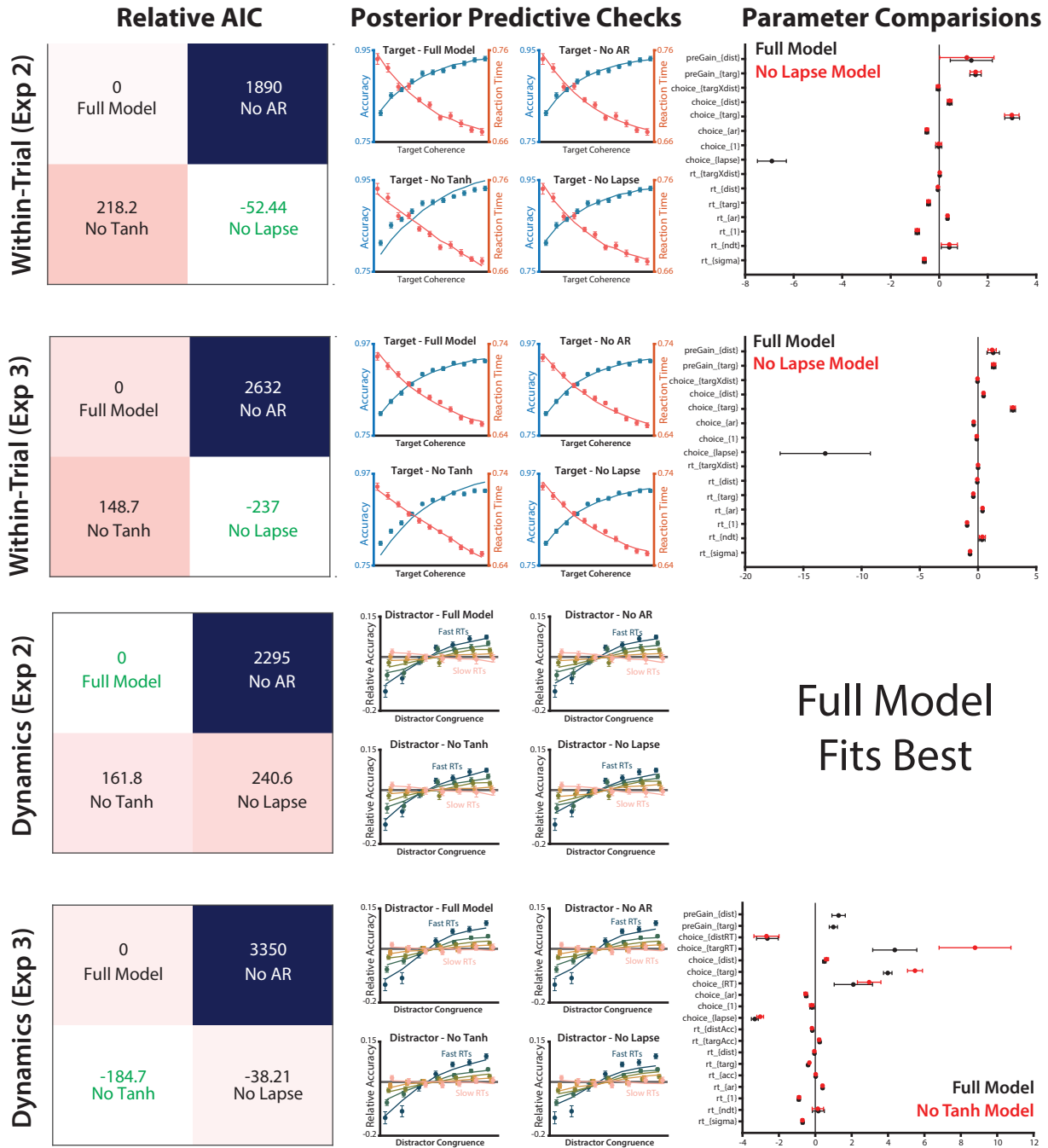
Within-Trial (Experiment 3)



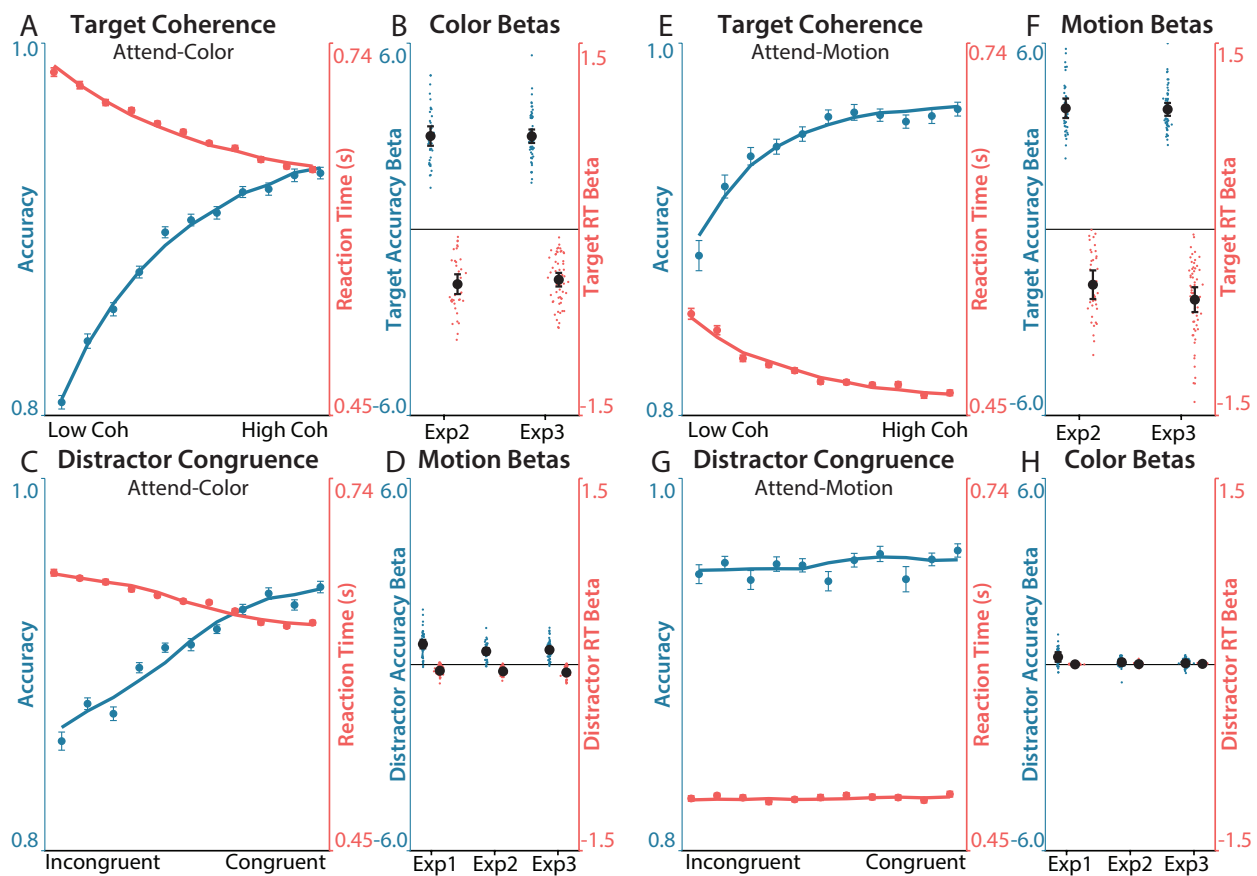
Dynamics (Experiment 3)



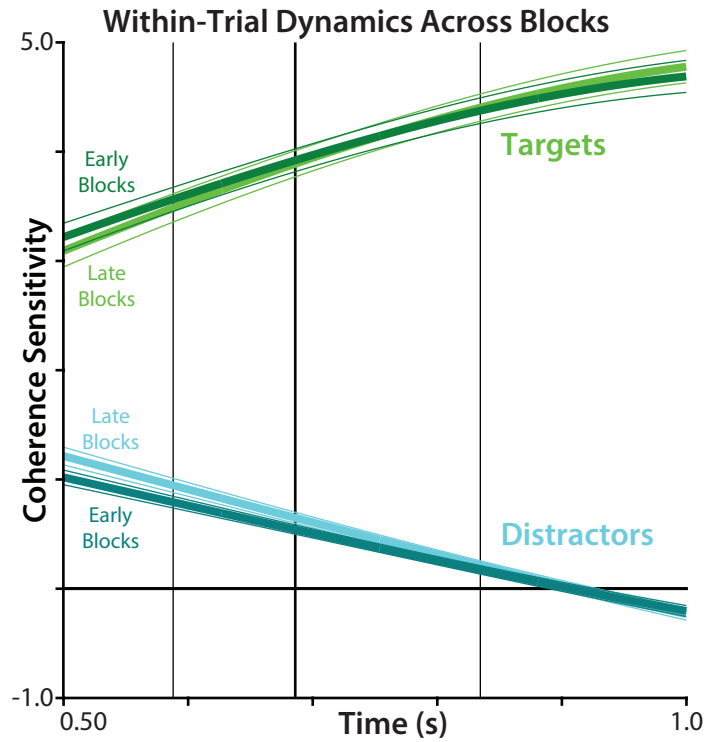
Supplementary Figure 8. Parameter Recovery. We simulated behavior from each participants' best-fitting parameters (x-axis) and then fit our model to this simulated behavior (y-axis). Each panel represents a parameter for the within-trial sensitivity model (top) and the within-trial dynamics model (bottom). Parameters were estimated hierarchically, with five simulated samples for each model (5 repetitions \times 60 simulated participants). Gray horizontal and vertical lines reflect the parameter zero point, and the diagonal cyan line reflects the unity line. The simulated-recovered parameter correlation is reported in each panel title.



Supplementary Figure 9. Parameter knock-out analysis. Relative AIC (left column): parameter-penalized model fits for the regression model in the main text ('Full Model'), a model with previous RT and Choice removed ('No AR'), a model with tanh nonlinearities removed ('No Tanh'), and a model with the lapse rate response ('No Lapse'). Smaller values reflect better fit, with zero reflecting the AIC of the full model. Posterior predictive checks (center column): simulated behavior (lines) plotted over observed behavior (dots). Notice that removing tanh nonlinearities fails to capture behavioral trends in within-subject models, and removing lapse terms fails to capture behavior in Dynamics models. Parameter comparisons (right column): model parameters plotted for the best-fitting model (red) and the full model (black). Notice that the parameters are very similar between these models, demonstrating that our key parameters are robust to knocking out other terms of the model.



Supplementary Figure 10. Target and distractor sensitivity (Equal Axes). A) Participants were more accurate (blue, left axis) and responded faster (red, right axis) when the target color had higher coherence. Lines depict aggregated regression predictions. In all graphs, behavior and regression predictions are averaged over participants and experiments. Data aggregated across Experiments 2 & 3. B) Regression estimates for the effect of target coherence on performance within each experiment, plotted for accuracy (blue, left axis) and RT (red, right axis). C) Participants were more accurate and responded faster when the distracting motion had higher congruence (coherence signed relative to target response). In all graphs, behavior and regression predictions are averaged over participants and experiments. Data aggregated across Experiments 1-3. D) Regression estimates for the effect of distractor congruence on performance within each experiment, plotted for accuracy and RT. E-F) Similar to A-B, performance (E) and regression estimates (F) for the effects of target coherence during Attend-Motion blocks, in which motion was the target dimension. G-H) Similar to A-B, performance (G) and regression estimates (H) for the effects of distractor congruence during Attend-Motion blocks, in which color was the distractor dimension. Error bars on behavior reflect within-participant SEM, error bars on regression coefficients reflect 95% CI. Psychometric functions are jittered on the x-axis for ease of visualization. Y-axes have been equalized across features and tasks.



Supplementary Figure 11: Changes in within-trial dynamics across blocks. Compared to earlier blocks, in later blocks participants' earliest sensitivity was weaker for targets and stronger for distractors (i.e., less task-appropriate later in the experiment). However, participants also exhibited faster corrected dynamics in later blocks, showing similar sensitivity for the slowest reaction times.

Supplementary Note: Task Instructions

Motion training

You will see dots that are moving left or right. If the dots are moving left, respond with the left key. If the dots are moving right, respond with the right key. If you are correct, you will be told so, and if you make a mistake, you will be reminded about the response mappings. As always, please respond as quickly and accurately as you can.

Color training

You will see dots that are one of *these* four colors. If the dots are *these* colors, respond with *this* hand. If the dots are *these* colors, respond with *this* hand. If you are correct, you will be told so, and if you make a mistake, you will get to see the colors again. As always, please respond as quickly and accurately as you can.

Main Experiment

This is the main section. Now you will see dots that both have a color and are moving left or right. There will be two kinds of blocks. This block is a color block. In this block, you will have to respond to color with these keys, like you did in the training. You will no longer receive feedback. Other blocks will be motion blocks, and you will have to respond based on the direction of the dot motion. Feel free to take a short break between blocks and come get me after you've finished all the blocks. As always, please respond as quickly and accurately as you can. (Note: during experiments 2 and 3, we emphasized choosing the color that was in the majority).

Reward Variant

During some of the color and motion blocks, you will be able to earn a monetary reward based on your performance. This block is one of the HIGH reward blocks. These blocks will say 'high reward' at the top, and the text will be gold. At the end of the experiment, we will randomly pick a bunch of trials from these blocks. Depending on how many trials that are fast and accurate, you will be able to earn up to \$4. Other blocks will be 'NO reward' blocks, with 'NO reward' written at the top and white text. You will not earn any money for your performance on these blocks.