Supplemental Methods & Results

Table S1
Simple Joint Model Parameter Estimates

	Experiment 1 n = 23			Experiment 2 n = 25		
	Hold	**Shift**	**Split**	**Hold**	**Shift**	**Split**
pT_CT_O	.871 (.086)	.901 (.075)	.746 (.118)	.726 (.171)	.811 (.136)	.645 (.199)
$pN1_CN1_O$	.010 (.017)	.028 (.034)	.007 (.023)	.017 (.024)	.036 (.040)	.009 (.010)
pT_CN1_O	.014 (.017)	.013 (.018)	.032 (.053)	.014 (.014)	.009 (.007)	.030 (.030)
$pN1_CT_O$	.005 (.009)	.004 (.003)	.003 (.004)	.008 (.008)	.015 (.017)	.007 (.009)
pT_CU_O	.015 (.014)	.015 (.016)	.069 (.042)	.043 (.048)	.038 (.057)	.091 (.096)
pU_CT_O	.015 (.015)	.012 (.020)	.077 (.070)	.050 (.068)	.036 (.043)	.110 (.115)
$pN1_CU_O$	.006 (.008)	.005 (.005)	.002 (.003)	.007 (.009)	.014 (.027)	.008 (.007)
pU_CN1_O	.006 (.007)	.007 (.008)	.008 (.006)	.007 (.006)	.009 (.012)	.019 (.030)
pU_CU_O	.057 (.068)	.016 (.021)	.055 (.048)	.128 (.148)	.033 (.039)	.080 (.078)
μ_C	1.35 (4.72)	-0.60 (5.38)	0.36 (5.93)	0.56 (4.92)	0.65 (3.21)	1.40 (6.14)
μ_O	0.33 (2.18)	0.35 (2.31)	0.16 (3.03)	0.46 (2.20)	0.50 (2.81)	0.43 (3.70)
σ_C	21.05 (5.31)	20.40 (5.70)	24.19 (6.73)	20.34 (4.26)	20.46 (3.12)	23.85 (5.91)
σ_O	12.30 (2.74)	12.20 (3.00)	17.52 (4.18)	14.90 (3.63)	15.39 (5.20)	16.61 (5.08)

Group means, with standard deviations presented in parentheses. μ_C and σ_C range from –180º to +180º, while μ_O and σ_O range from –90º to +90º ($\sigma = \sqrt{1/\kappa}$)

Table S2
Full Joint Model Parameter Estimates

	Experiment 1 n = 23			Experiment 2 n = 25		
	Hold	**Shift**	**Split**	**Hold**	**Shift**	**Split**
pT_CT_O	.886 [.867 .892]	.904 [.895 .920]	.748 [.702 .755]	.755 [.733 .777]	.815 [.792 .833]	.688 [.635 .715]
$pN1_CN1_O$	.013 [.008 .018]	.028 [.021 .032]	.007 [.002 .009]	.019 [.014 .028]	.033 [.024 .041]	.011 [.004 .017]
$pN2_CN2_O$	.013 [.009 .018]	.001 [.000 .004]	.009 [.004 .012]	.021 [.014 .026]	.003 [.001 .006]	.006 [.002 .014]
$pN3_CN3_O$	.013 [.008 .016]	.000 [.000 .002]	.001 [.000 .003]	.028 [.021 .037]	.001 [.000 .003]	.000 [.000 .004]
pT_CN1_O	.011 [.009 .021]	.014 [.008 .020]	.062 [.042 .075]	.013 [.000 .024]	.015 [.002 .027]	.036 [.006 .058]
$pN1_CT_O$	.009 [.004 .012]	.006 [.003 .011]	.005 [.000 .008]	.006 [.001 .011]	.014 [.005 .020]	.003 [.000 .007]
pT_CN2_O	.013 [.009 .021]	.005 [.003 .013]	.061 [.041 .077]	.020 [.006 .033]	.015 [.005 .032]	.022 [.003 .042]
$pN2_CT_O$	.009 [.004 .014]	.007 [.004 .011]	.025 [.015 .028]	.008 [.004 .014]	.013 [.007 .019]	.017 [.010 .023]
pT_CN3_O	.001 [.000 .003]	.000 [.000 .004]	.023 [.001 .031]	.001 [.000 .014]	.003 [.000 .009]	.018 [.000 .035]
$pN3_CT_O$	.001 [.000 .003]	.000 [.000 .001]	.005 [.001 .007]	.005 [.000 .009]	.002 [.000 .003]	.002 [.000 .008]
$pN1_CN2_O$	.000 [.000 .001]	.000 [.000 .001]	.001 [.000 .001]	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .003]
$pN2_CN1_O$	.000 [.000 .001]	.000 [.000 .001]	.001 [.000 .001]	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .003]
$pN1_CN3_O$	.000 [.000 .001]	.000 [.000 .001]	.001 [.000 .001]	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .003]
$pN3_CN1_O$	.000 [.000 .001]	.000 [.000 .001]	.001 [.000 .001]	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .003]
$pN2_CN3_O$	.001 [.000 .002]	.000 [.000 .002]	.003 [.000 .005]	.003 [.000 .004]	.001 [.000 .003]	.002 [.000 .007]
$pN3_CN2_O$	.001 [.000 .001]	.000 [.000 .002]	.003 [.000 .005]	.003 [.000 .004]	.001 [.000 .003]	.002 [.000 .007]
pT_CU_O	.001 [.000 .018]	.002 [.000 .011]	.015 [.000 .061]	.025 [.002 .089]	.041 [.000 .068]	.031 [.000 .157]
pU_CT_O	.013 [.000 .014]	.017 [.000 .017]	.017 [.000 .076]	.063 [.000 .067]	.015 [.000 .054]	.085 [.000 .147]
$pN1_CU_O$	.003 [.000 .007]	.001 [.000 .004]	.002 [.000 .006]	.003 [.000 .011]	.018 [.005 .026]	.006 [.000 .017]
pU_CN1_O	.008 [.000 .010]	.000 [.000 .009]	.006 [.000 .012]	.009 [.000 .014]	.001 [.000 .008]	.005 [.000 .018]
$pN2_CU_O$	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .004]	.001 [.000 .004]	.000 [.000 .002]	.000 [.000 .006]
pU_CN2_O	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .004]	.001 [.000 .004]	.000 [.000 .002]	.000 [.000 .006]
$pN3_CU_O$	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .004]	.001 [.000 .004]	.000 [.000 .002]	.000 [.000 .006]
pU_CN3_O	.000 [.000 .002]	.001 [.000 .002]	.001 [.000 .004]	.001 [.000 .004]	.000 [.000 .002]	.000 [.000 .006]
pU_CU_O	.002 [.000 .014]	.011 [.000 .011]	.000 [.000 .023]	.009 [.000 .046]	.006 [.000 .013]	.063 [.001 .069]
μ_C	0.98 [0.27 1.95]	-0.12 [-0.98 0.39]	-0.06 [-1.06 0.60]	1.59 [0.22 1.82]	0.42 [-0.18 1.36]	1.65 [1.21 3.18]
μ_O	0.27 [-0.20 0.92]	0.42 [-0.04 0.86]	0.38 [-0.40 0.94]	0.04 [-0.68 0.60]	0.00 [-0.78 0.76]	-0.67 [-1.08 0.91]
σ_C	20.98 [20.51 21.90]	20.44 [19.57 20.83]	23.63 [22.69 24.18]	21.52 [20.66 22.01]	20.36 [19.58 21.08]	23.35 [22.25 24.22]
σ_O	12.36 [11.93 12.87]	12.23 [11.65 12.51]	15.63 [14.53 16.13]	14.70 [14.11 15.63]	14.48 [13.93 15.25]	16.94 [15.69 18.01]

Maximum-likelihood estimates, with 95% highest density intervals presented in brackets. μ_C and σ_C range from –180º to +180º, while μ_O and σ_O range from –90º to +90º ($\sigma = \sqrt{1/\kappa}$)

Table S3

Summary of Comparisons for pT_CT_O, σ_C and σ_O (Simple Model)

Experiment 1		Test Statistic	Significance	Effect size
$\boldsymbol{pT_CT_O}$	Omnibus ANOVA	$F(2, 44) = 21.5$	$p < .001$*	$\eta^2 = .495$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(22) = 4.20$	$p < .001$**	$d = 0.88$
	Shift vs. Split	$t(22) = 6.78$	$p < .001$**	$d = 1.42$
	Hold vs. Shift	$t(22) = 1.36$	$p = .189$	$d = 0.28$
$\boldsymbol{\sigma_C}$	Omnibus ANOVA	$F(2, 44) = 13.1$	$p < .001$*	$\eta^2 = .372$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(22) = 4.47$	$p < .001$**	$d = 0.93$
	Shift vs. Split	$t(22) = 4.48$	$p < .001$**	$d = 0.93$
	Hold vs. Shift	$t(22) = 0.79$	$p = .439$	$d = 0.16$
$\boldsymbol{\sigma_O}$	Omnibus ANOVA	$F(2, 44) = 32.6$	$p < .001$*	$\eta^2 = .597$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(22) = 5.84$	$p < .001$**	$d = 1.22$
	Shift vs. Split	$t(22) = 6.43$	$p < .001$**	$d = 1.34$
	Hold vs. Shift	$t(22) = 0.21$	$p = .836$	$d = 0.04$

Experiment 2		Test Statistic	Significance	Effect size
$\boldsymbol{pT_CT_O}$	Omnibus ANOVA	$F(2, 48) = 12.9$	$p < .001$*	$\eta^2 = .349$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(24) = 2.30$	$p = .031$	$d = 0.46$
	Shift vs. Split	$t(24) = 5.42$	$p < .001$**	$d = 1.08$
	Hold vs. Shift	$t(24) = 2.65$	$p = .014$**	$d = 0.53$
$\boldsymbol{\sigma_C}$	Omnibus ANOVA	$F(2, 48) = 9.54$	$p < .001$*	$\eta^2 = .284$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(24) = 2.99$	$p = .006$**	$d = 0.60$
	Shift vs. Split	$t(24) = 3.81$	$p < .001$**	$d = 0.76$
	Hold vs. Shift	$t(24) = 0.21$	$p = .835$	$d = 0.04$
$\boldsymbol{\sigma_O}$	Omnibus ANOVA	$F(2, 48) = 0.79$	$p = .461$	$\eta^2 = .032$
	Post-hoc t-*tests*			
	Hold vs. Split	$t(24) = 1.19$	$p = .246$	$d = 0.24$
	Shift vs. Split	$t(24) = 0.70$	$p = .492$	$d = 0.14$
	Hold vs. Shift	$t(24) = 0.55$	$p = .586$	$d = 0.11$

* denotes statistical significance at $p < .05$

** denotes statistical significance at $p < .017$ (Bonferroni-corrected for multiple post-hoc comparisons)

Table S4

Summary of Comparisons for Proportions of Non-T_CT_O Errors (Simple Model)

Experiment 1	Factor	Test Statistic	Significance	Effect size
Omnibus ANOVA	Condition	$F(2, 44) = 13.7$	$p < .001$*	$\eta^2 = .384$
	Error Type ($N1_CN1_O$ vs. Independent T*)	$F(1, 22) = 147.9$	$p < .001$*	$\eta^2 = .871$
	Interaction	$F(2, 44) = 23.3$	$p < .001$*	$\eta^2 = .515$
Post-hoc *t*-tests	Hold-N1N1 vs. Shift-N1N1	$t(22) = 4.21$	$p < .001$**	$d = 0.88$
	Hold-N1N1 vs. Split-N1N1	$t(22) = 2.02$	$p = .055$	$d = 0.42$
	Shift-N1N1 vs. Split-N1N1	$t(22) = 5.78$	$p < .001$**	$d = 1.21$
	Hold-Ind vs. Shift-Ind	$t(22) = 0.10$	$p = .920$	$d = 0.02$
	Hold-Ind vs. Split-Ind	$t(22) = 6.57$	$p < .001$**	$d = 1.37$
	Shift-Ind vs. Split-Ind	$t(22) = 5.10$	$p < .001$**	$d = 1.06$

Experiment 2	Factor	Test Statistic	Significance	Effect size
Omnibus ANOVA	Condition	$F(2, 48) = 7.85$	$p = .001$	$\eta^2 = .246$
	Error Type ($N1_CN1_O$ vs. Independent T*)	$F(1, 24) = 144.98$	$p < .001$*	$\eta^2 = .858$
	Interaction	$F(2, 48) = 5.32$	$p = .008$*	$\eta^2 = .181$
Post-hoc *t*-tests	Hold-N1N1 vs. Shift-N1N1	$t(24) = 4.23$	$p < .001$**	$d = 0.846$
	Hold-N1N1 vs. Split-N1N1	$t(24) = 0.72$	$p = .479$	$d = 0.14$
	Shift-N1N1 vs. Split-N1N1	$t(24) = 4.42$	$p < .001$**	$d = 0.885$
	Hold-Ind vs. Shift-Ind	$t(24) = 0.98$	$p = .338$	$d = 0.20$
	Hold-Ind vs. Split-Ind	$t(24) = 2.88$	$p = .008$**	$d = 0.58$
	Shift-Ind vs. Split-Ind	$t(24) = 1.85$	$p = .077$	$d = 0.37$

* denotes statistical significance at $p < .05$

** denotes statistical significance at $p < .0083$ (Bonferroni-corrected for multiple post-hoc comparisons)

S5. Comparison of Simple Model versus Full Model

The Simple Model was designed to reduce the number of parameters and only includes separate von Mises distributions centered on T_C, T_O, $N1_C$, and $N1_O$. In contrast, the Full Model includes separate von Mises distributions centered on T_C, T_O, $N1_C$, $N1_O$, $N2_C$, $N2_O$, $N3_C$, and $N3_O$. Because the Simple Model does not explicitly model *N2* and *N3*, any responses that would fall into those distributions under the Full Model should be absorbed by U_C and U_O in the Simple Model. To align and compare response types across the Simple and Full Models, the parameters must be grouped appropriately. For example, the T_CU_O component in the Simple Model is not directly equivalent to the T_CU_O component in the Full Model, but rather is equivalent to the sum of T_CU_O, T_CN2_O, and T_CN3_O.

Table S5

Comparison of Response Types across Simple Model versus Full Model

	Simple Model				**Full Model**			
Experiment 1	**Parameters Included**	**Hold**	**Shift**	**Split**	**Parameters Included**	**Hold**	**Shift**	**Split**
Correlated target	pT_CT_O	.871 (.086)	.901 (.075)	.746 (.118)	pT_CT_O	.886 [.867 .892]	.904 [.895 .920]	.748 [.702 755]
Correlated $N1_CN1_O$ swap	$pN1_CN1_O$	.010 (.017)	.028 (.034)	.007 (.023)	$pN1_CN1_O$	.013 [.008 .018]	.028 [.021 .032]	.007 [.002 .009]
Illusory target conjunction	pT_CN1_O + $pN1_CT_O$	.019 (.017)	.017 (.019)	.036 (.052)	pT_CN1_O + $pN1_CT_O$	.020 [.015 .030]	.020 [.013 .028]	.067 [.045 .079]
Unbound target guess	pT_CU_O + pU_CT_O	.030 (.021)	.026 (.032)	.147 (.067)	pT_CU_O + pT_CN2_O + pT_CN3_O + pU_CT_O + $pN2_CT_O$ + $pN3_CT_O$	.038 [.029 .051]	.038 [.019 .037]	.146 [.127 .195]
Experiment 2	**Parameters Included**	**Hold**	**Shift**	**Split**	**Parameters Included**	**Hold**	**Shift**	**Split**
Correlated target	pT_CT_O	.726 (.171)	.811 (.136)	.645 (.199)	pT_CT_O	.755 [.733 .777]	.815 [.792 .833]	.688 [.635 .715]
Correlated $N1_CN1_O$ swap	$pN1_CN1_O$	.017 (.024)	.036 (.040)	.009 (.010)	$pN1_CN1_O$	.019 [.014 .028]	.033 [.024 .041]	.011 [.004 .017]
Illusory target conjunction	pT_CN1_O + $pN1_CT_O$	.022 (.016)	.023 (.018)	.038 (.032)	pT_CN1_O + $pN1_CT_O$	.019 [.005 .032]	.029 [.013 .044]	.039 [.012 .065]
Unbound target guess	pT_CU_O + pU_CT_O	.093 (.095)	.074 (.081)	.201 (.167)	pT_CU_O + pT_CN2_O + pT_CN3_O + pU_CT_O + $pN2_CT_O$ + $pN3_CT_O$	.122 [.081 .139]	.089 [.070 .112]	.175 [.141 .237]

Group means, with standard deviations in parentheses, for Simple Model; maximum-likelihood estimates, with 95% highest density intervals in brackets, for Full Model

S6. Feature Prioritization when Splitting Attention

As reported in the main text, in Split trials, unbound guesses ($T_CU_O + U_CT_O$, Simple Model) occurred more often than illusory conjunctions ($T_CN1_O + N1_CT_O$, Simple Model)**,** $t(22) = 7.78$, $p < .001$, $d = 1.62$ (Experiment 1), $t(24) = 6.09$, $p < .001$, $d = 1.22$ (Experiment 2), suggesting that one feature dimension was prioritized such that participants reported only one feature of the target and guessed the other. Was one feature dimension (i.e., color or orientation) *systematically* prioritized over the other? Across participants, no single feature was consistently prioritized (Table S6A). However, most individual participants did seem to prioritize one feature dimension. Figure S6A plots individual parameter estimates of pT_CU_O and pU_CT_O for the Split condition. In a verbal debriefing after the Split session, 16 of 23 participants in Experiment 1 and 17 of 25 participants in Experiment 2 noted that reporting color was easier than reporting orientation, which was not significantly different from chance, $\chi^2(1) = 2.78$, $p = .095$ and $\chi^2(1) = 2.56$, $p = .110$.

Table S6A

Group-level Comparison of T_CU_O versus U_CT_O

	Simple Model		**Full Model**[1]	
Unbound "TU"	**Mean (SD)**	**Statistic**	**Mean [95% HDI]**	**HDI overlap?**
Experiment 1	$pT_CU_O = .069$ (.042)	$t(22) = 0.40$, $p = .690$, $d = 0.08$	$pT_CU_O + pT_CN2_O + pT_CN3_O = .099$, [.069 .139]	Yes: Not significantly different
	$pU_CT_O = .077$ (.070)		$pU_CT_O + pN2_CT_O + pN3_CT_O = .047$, [.024 .103]	
Experiment 2	$pT_CU_O = .091$ (.096)	$t(24) = 0.73$, $p = .475$, $d = 0.15$	$pT_CU_O + pT_CN2_O + pT_CN3_O = .072$, [.031 .178]	Yes: Not significantly different
	$pU_CT_O = .110$ (.115)		$pU_CT_O + pN2_CT_O + pN3_CT_O = .103$, [.024 .172]	

[1] In Split trials, illusory conjunctions ($T_CN1_O + N1_CT_O$) are restricted to T and N1 items only, because those are the two cued items of interest. The N2 and N3 items are theoretically less relevant since neither was ever cued, so the T_CN2_O, $N2_CT_O$, T_CN3_O, and $N3_CT_O$ are treated as unbound "TU" responses for this analysis.

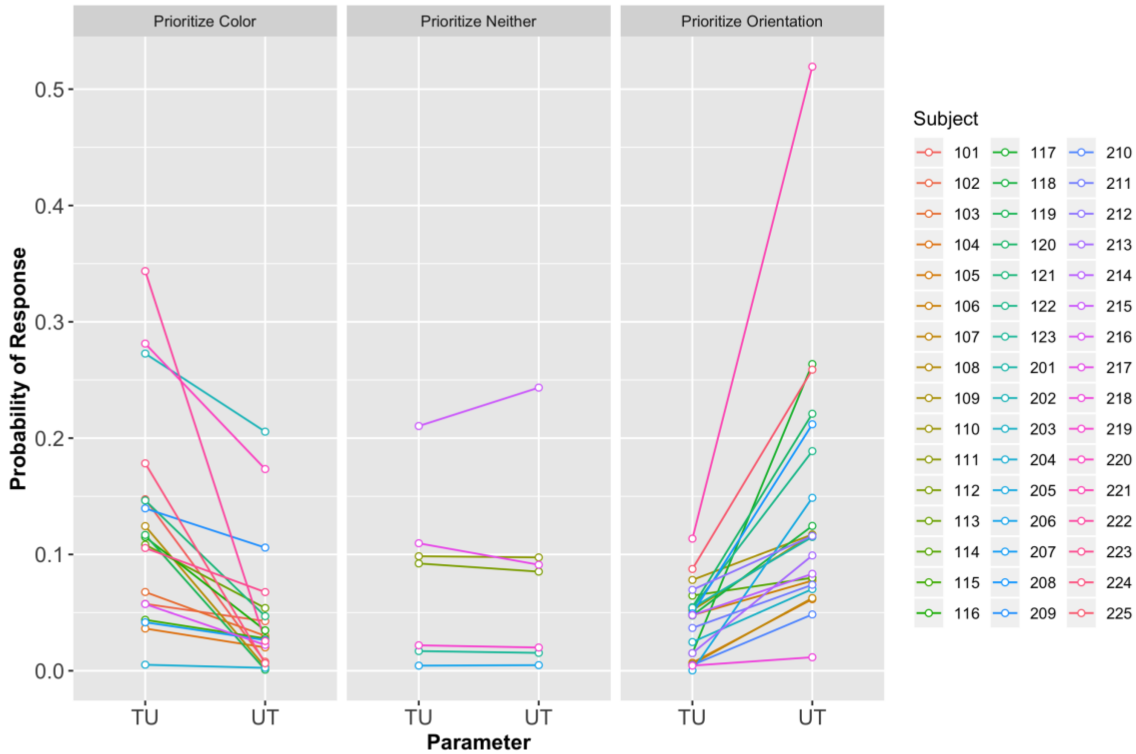

Figure S6A. Individual participants' pT_CU_O and pU_CT_O parameter estimates (unbound guesses; Simple Model) for the Split condition across both experiments. Each color represents an individual participant (subjects 101–123 for Experiment 1 and 201–225 for Experiment 2), and the connecting lines illustration the direction of prioritization. Participants are divided into three groups: those who prioritize color ($pT_CU_O > pU_CT_O$ by at least 10%; left), those who prioritize neither (<10% difference between pT_CU_O and pU_CT_O; middle), and those who prioritize orientation ($pT_CU_O < pU_CT_O$ by at least 10%; right).

The above analyses are for unbound guesses—what about illusory conjunctions? In Split trials, illusory conjunctions made up a small proportion of all non-T_CT_O errors (12.7% in both Experiments, Simple Model). However, across participants, illusory conjunctions of the target color and the critical N1 orientation (T_CN1_O) were significantly more likely than illusory conjunctions of the target orientation and the critical N1 color ($N1_CT_O$; Table S6B). Likewise, most individual participants exhibited this feature asymmetry in illusory conjunctions (Figure S6B).

Table S6B

Group-level Comparison of T_CN1_O versus $N1_CT_O$

	Simple Model		**Full Model**	
Illusory "TN1"	**Mean (SD)**	**Statistic**	**Mean [95% HDI]**	**HDI overlap?**
Experiment 1	pT_CN1_O = .032 (.053)	*t*(22) = 2.60, *p* = .016,**, *d* = 0.54	pT_CN1_O = .062, [.042 .075]	No: Significantly different
	$pN1_CT_O$ = .003 (.004)		$pN1_CT_O$ = .005, [.000 .008]	
Experiment 2	pT_CN1_O = .030 (.030)	*t*(24) = 3.77, *p* < .001,**, *d* = 0.76	pT_CN1_O = .036, [.006 .058]	Yes: Not significantly different
	$pN1_CT_O$ = .007 (.009)		$pN1_CT_O$ = .003, [.000 .007]	

** denotes statistical significance at *p* < .025 (Bonferroni-corrected for multiple comparisons)

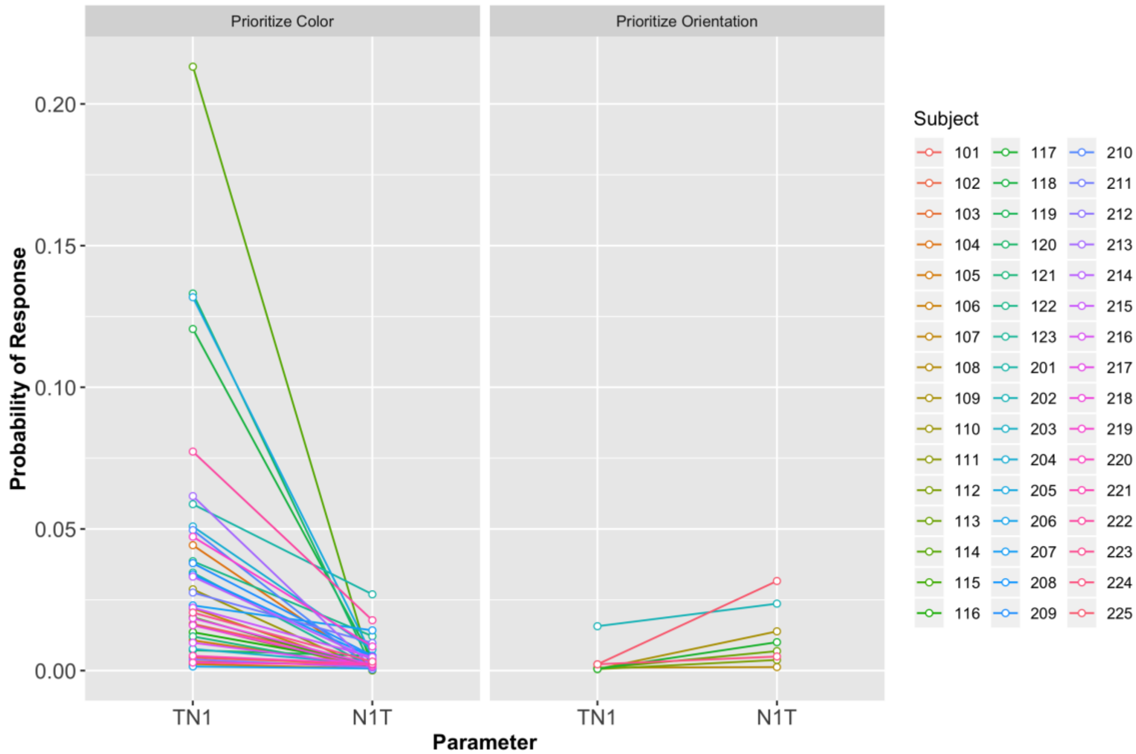

Figure S6B. Individual participants' $pT_C N1_O$ and $pN1_C T_O$ parameter estimates (illusory conjunctions; Simple Model) for the Split condition across both experiments. Each color represents an individual participant, and the connecting lines illustration the direction of prioritization. Participants are divided into two groups: those who prioritize color ($pT_C N1_O$ > $pN1_C T_O$ by at least 10%; left), and those who prioritize orientation ($pT_C N1_O$ < $pN1_C T_O$ by at least 10%; right). No subjects were classified as prioritizing neither feature (10% difference between $pT_C N1_O$ and $pN1_C T_O$).

S7. Is There a Bilateral Field Advantage in Dynamic Attention?

To examine the possibility of a bilateral visual field advantage within our paradigm, we fit the Full Joint Model to two subsets of Experiment 1 Split data: A) when the two cued locations fell in left and right visual fields (i.e., horizontally adjacent cues) versus B) when the two cued locations both fell within left visual field or within right visual field (i.e., vertically adjacent cues). We also performed the same analysis for Experiment 1 Shift data, subsetting trials by the direction from the initial cue to the second shift cue (i.e., horizontal vs. vertical shift). Based on the parameter estimates' 95% HDIs (Table S7, considered significantly different if they do not overlap; Kruschke, 2011), performance when splitting attention horizontally was not significantly different from splitting attention vertically. There were also no significant differences in performance when shifting attention horizontally or vertically.

It is likely that the current paradigm was not sufficiently spatially demanding to produce a significant bilateral advantage; for instance, a bilateral field advantage has been demonstrated with multiple-object tracking (e.g., Alvarez & Cavanagh, 2005) and has been found for a spatial working memory task, but not a color working memory task (Delvenne, 2005). Golomb (2015), which used a similar paradigm as the current task to examine splits of spatial attention across two locations, also found no bilateral field advantage. However, it is worth noting that while none of these comparisons passed significance according to 95% HDIs, correlated target responses were numerically lower in vertical Split and Shift trials compared to horizontal Split and Shift trials, consistent with a bilateral field benefit for divided attention. Due to lower trial counts, we could not fit the Simple Model to the subsets of Split data or Shift data for each individual subject; however, future experiments designed to examine hemifield effects could better address this question.

Table S7

Experiment 1 Full Joint Model Parameter Estimates, by Visual Field

SPLIT		
Response type	**Horizontal Split**	**Vertical Split**
Correlated target (pT_CT_O)	.743 [.725 .796]	.705 [.660 .731]
Correlated N1N1 ($pN1_CN1_O$)	.003 [.000 .009]	.011 [.001 .013]
Illusory target (pT_CN1_O, $pN1_CT_O$)	.061 [.024 .072]	.075 [.043 .088]
Unbound target (pT_CU_O, pU_CT_O)	.083 [.022 .140]	.028 [.022 .137]
SHIFT		
Response type	**Horizontal Shift**	**Vertical Shift**
Correlated target (pT_CT_O)	.921 [.887 .923]	.904 [.879 .914]
Correlated N1N1 ($pN1_CN1_O$)	.024 [.017 .035]	.025 [.016 .035]
Illusory target (pT_CN1_O, $pN1_CT_O$)	.017 [.010 .030]	.016 [.006 .026]
Unbound target (pT_CU_O, pU_CT_O)	.005 [.001 .020]	.006 [.002 .029]

Maximum-likelihood estimates, with highest density intervals presented in brackets

Table S8
Location Model Parameter Estimates

	Experiment 2 n = 25	
	Hold	**Shift**
pT_L	.887 (.137)	.920 (.081)
$pN1_L$	.028 (.042)	.052 (.067)
$pN2_L$	.025 (.044)	.006 (.012)
$pN3_L$	.037 (.044)	.003 (.005)
pU_L	.023 (.035)	.019 (.022)
μ_L	0.00 (1.41)	0.47 (1.55)
σ_L	9.02 (1.76)	9.31 (1.31)

Group means, with standard deviations presented in parentheses. μ_L and σ_L range from –180º to +180º ($\sigma = \sqrt{1/\kappa}$)

Table S9
Summary of Comparisons for Location Model (Experiment 2)

	Factor	Test Statistic	Significance	Effect size
Omnibus ANOVA	Condition	$F(1, 24) = 1.45$	$p = .240$	$\eta^2 = .057$
	Error Type (N1, N2, N3)	$F(3, 72) = 6.14$	$p < .001$*	$\eta^2 = .204$
	Interaction	$F(3, 72) = 8.40$	$p < .001$*	$\eta^2 = .259$
Post-hoc *t*-tests	Hold-N1 vs. Hold-N2	$t(24) = 0.49$	$p = .627$	$d = 0.10$
	Hold-N1 vs. Hold-N3	$t(24) = 1.49$	$p = .148$	$d = 0.30$
	Hold N2 vs. Hold-N3	$t(24) = 1.44$	$p = .162$	$d = 0.29$
	Shift-N1 vs. Shift-N2	$t(24) = 3.66$	$p = .001$**	$d = 0.73$
	Shift-N1 vs. Shift-N3	$t(24) = 3.74$	$p = .001$**	$d = 0.75$
	Shift-N2 vs. Shift-N3	$t(24) = 1.61$	$p = .120$	$d = 0.32$

* denotes statistical significance at $p < .05$
** denotes statistical significance at $p < .0083$ (Bonferroni-corrected for multiple post-hoc comparisons)

Table S10

Triple Joint Model Parameter Estimates

	Experiment 2 n = 25	
	Hold	**Shift**
$pT_CT_OT_L$	.856 [.835 .862]	.898 [.879 .904]
$pN1_CN1_OT_L$	.001 [.000 .004]	.000 [.000 .002]
$pN2_CN2_OT_L$	.004 [.000 .006]	.000 [.000 .002]
$pN3_CN3_OT_L$	.000 [.000 .002]	.000 [.000 .001]
$pU_CU_OT_L$	.039 [.029 .056]	.034 [.028 .047]
$pT_CT_ON1_L$	.002 [.000 .005]	.001 [.000 .004]
$pN1_CN1_ON1_L$	.022 [.020 .029]	.040 [.033 .050]
$pN2_CN2_ON1_L$	.000 [.000 .001]	.000 [.000 .001]
$pN3_CN3_ON1_L$	.000 [.000 .002]	.000 [.000 .002]
$pU_CU_ON1_L$	.006 [.001 .009]	.013 [.008 .017]
$pT_CT_ON2_L$	.004 [.002 .006]	.002 [.000 .004]
$pN1_CN1_ON2_L$	.001 [.000 .002]	.000 [.000 .001]
$pN2_CN2_ON2_L$	.024 [.017 .030]	.002 [.001 .006]
$pN3_CN3_ON2_L$	.001 [.000 .002]	.000 [.000 .001]
$pU_CU_ON2_L$	.003 [.000 .005]	.003 [.000 .005]
$pT_CT_ON3_L$	.000 [.000 .002]	.001 [.000 .004]
$pN1_CN1_ON3_L$	.000 [.000 .001]	.000 [.000 .001]
$pN2_CN2_ON3_L$	.001 [.000 .002]	.000 [.000 .001]
$pN3_CN3_ON3_L$	.033 [.026 .039]	.001 [.000 .001]
$pU_CU_ON3_L$	.004 [.002 .009]	.002 [.000 .003]
σ_C	21.53 [20.76 22.28]	20.50 [20.24 21.56]
σ_O	21.07 [19.68 21.43]	18.15 [17.74 19.39]
σ_L	9.84 [9.50 10.12]	10.04 [9.75 10.27]

Maximum-likelihood estimates, with 95% highest density intervals presented in brackets. σ_C and σ_L range from –180º to +180º, while σ_O ranges from –90º to +90º ($\sigma = \sqrt{1/\kappa}$)

S11. Does the Precision of Location Report Predict Object-Feature Binding?

How important is the *precision* of spatial attention for object-feature binding? In the main text, we report results from Experiment 2 showing that location reports (coarsely defined) predict bound feature reports. Here we add a supplemental analysis examining whether the *magnitude* of location error (i.e., a proxy for the precision of spatial attention) was related to the probability of reporting the bound target item. We collapsed data across all subjects and included only Hold or Shift trials with location report errors between [–45º 45º] around the actual target location (Figure S11A,C). To simplify the analysis, we fit a basic joint-feature model that attributed responses only to T or U in each feature dimension, resulting in 4 response combinations (T_CT_O, T_CU_O, U_CT_O, U_CU_O) plus 2 parameters for concentrations κ_C and κ_O. This model did not include parameters for non-target items because as the Triple Model results indicate, there were negligible misreports of the non-target features when reporting T_L (see Figure 6 in main text). Thus, the goal was to compare the probability of correlated target responses (pT_CT_O) versus the probability of independent target errors ($pT_CU_O + pU_CT_O$).

This basic joint-feature model was iteratively fit to an expanding subset of trials, starting with trials with perfectly accurate location reports (location error = 0º) and expanding the window of location error by +/–5º until [–45º 45º]. For example, Bin 0º includes only trials with a location error of 0º, and Bin 5º includes trials with a location error ranging from –5º to +5º, inclusive of the trials from Bin 0º. The model was fit 10 times for each condition, resulting in 10 sets of parameter estimates that reflect the marginal effects of less precise spatial reports. We then ran a simple linear regression between the window of location error (i.e., +/– 0º to 45º) and the corresponding pT_CT_O parameters, for Hold trials and for Shift trials separately (Figure S11B). For both Hold and Shift trials, as location error increased, correlated target responses decreased and the corresponding sum of $pT_CU_O + pU_CT_O$ (i.e., unbound target errors) increased (Table S11). However, it should be noted that, particularly for Hold trials, the *slope* of the linear relationship was strongly determined by the first Bin 0º, where location reports were perfectly accurate. Specifically, when we re-ran the linear regression models without Bin 0º (i.e., including only Bins 5º–45º), the relationship between spatial precision and object-feature binding became more shallow and incremental (Table S11).

To further probe the importance of Bin 0º, we ran a similar analysis in which trials were binned more proportionately, expanding the window of location error by +/–2.25º (the lowest resolution possible with these data) at first, then by greater steps farther out from 0º. This way, the marginal effects of less precise spatial reports would be more comparable, as each expansion added approximately the same number of new trials (Figure S11C). As before, we assessed the relationship between the window of location error and the corresponding pT_CT_O and ($pT_CU_O + pU_CT_O$) parameters, for Hold trials and for Shift trials separately (Figure S11D). Again, for both conditions, as location error increased (log-transformed), correlated target responses decreased and unbound target errors increased (Table S11). The significant logarithmic fit emphasizes how important that first bin of 0º location error was in determining the slope of this relationship, showing that the effect of spatial precision did become more incremental outside the most precise location window (Figure S11D).

Overall, these results demonstrate a significant relationship between the precision of spatial location reports and the degree of non-spatial object-feature binding, supporting our hypothesis that the spatial extent of visual attention plays a critical role in the successful integration of non-spatial features. However, the effect is most pronounced at a location error of 0º, such that absolute spatial precision is a strong predictor of successful object-feature binding, but location errors beyond that only incrementally impact object-feature binding.

The interpretation of these supplementary analyses is limited by a few important factors: First, these analyses measure the "precision of spatial attention" with a location report—the accuracy of which could be impaired by an intervening delay and sub-task (e.g., the joint color and orientation report could take up to 10 s), and the resolution of which was limited by response steps of 2.25º. Second, these analyses collapsed data across participants, such that relationships between location error and parameter estimates could be driven by across-subject variance. While it would be ideal to run these analyses at the individual subject-level, there were not enough data to bin within subjects.

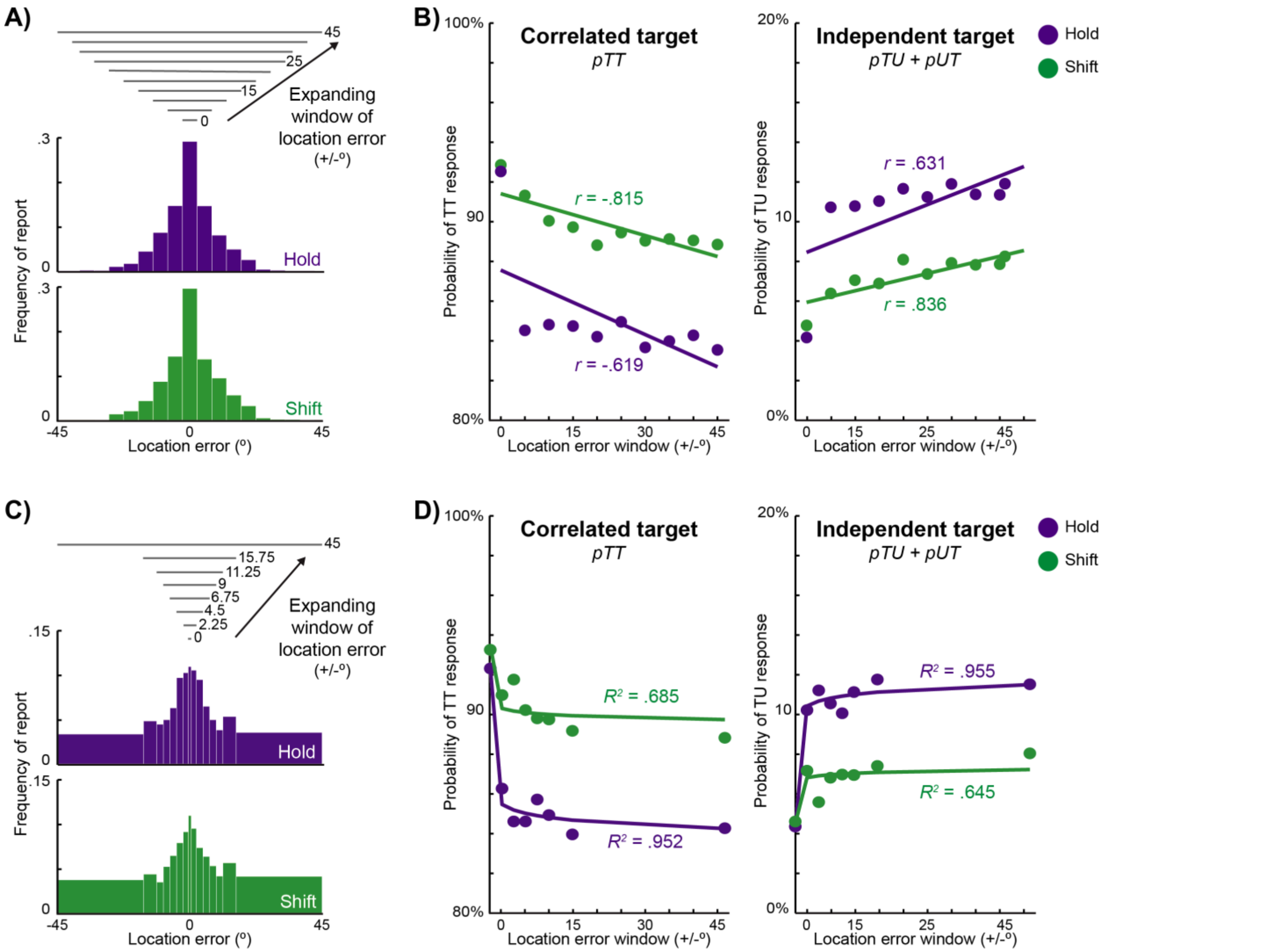

Figure S11. Linear and logarithmic relationships between the magnitude of location report error (i.e., a proxy for the *precision* of spatial attention) and non-spatial object-feature binding. This analysis was restricted to trials in Experiment 2 with location errors of [–45º 45º], as depicted in the histograms in (A,C). A simplified joint-feature model ($pT_CT_O + pT_CU_O + pU_CT_O + pU_CU_O$) was iteratively fit to color and orientation responses within expanding, inclusive windows of location errors (horizontal gray lines). The graphs in (B,D) plot the proportion of correlated target responses (left) and independent target responses (right).

Table S11

Linear Regression between Location Error Window and Bound or Unbound Responses

		Correlated TT		Independent TU|UT	
		Statistic	*Slope (%)*	*Statistic*	*Slope (%)*
Hold	Bins 0º–45º (steps of 5º)	*F*(1,8) = 4.98, *p* = .056, R^2adj = .307	–0.11	*F*(1,8) = 5.30, *p* = .050, R^2adj = .323	0.10
	Bins 5º–45º (steps of 5º)	*F*(1,7) = 6.37, *p* = .040, R^2adj = .402	–0.03	*F*(1,7) = 10.0, *p* = .016, R^2adj = .529	0.02
	Log_{10} (Bins 0º–45º, proportionate)	*F*(1,6) = 138.5, *p*< .001, R^2adj = 0.952	–1.25	*F*(1,6) = 151, *p* < .001, R^2adj = 0.955	1.10
Shift	Bins 0º–45º (steps of 5º)	*F*(1,8) = 15.8, *p* = .004, R^2adj = .622	–0.07	*F*(1,8) = 18.7, *p* = .003, R^2adj = .663	0.06
	Bins 5º–45º (steps of 5º)	*F*(1,7) = 11.6, *p* = .011, R^2adj = .569	–0.05	*F*(1,7) = 17.2, *p* = .004, R^2adj = .669	0.04
	Log_{10} (Bins 0º–45º, proportionate)	*F*(1,6) = 16.2, *p* = .007, R^2adj = 0.685	–0.59	*F*(1,6) = 13.7, *p* = .010, R^2adj = 0.645	0.42

Supplementary References

Alvarez, G. A., & Cavanagh, P. (2005). Independent resources for attentional tracking in the left and right visual hemifields. *Psychological Science*, *16*(8), 637-643.

Delvenne, J. F. (2005). The capacity of visual short-term memory within and between hemifields. *Cognition*, *96*(3), B79-B88.

Golomb, J. D. (2015). Divided spatial attention and feature-mixing errors. *Attention, Perception, & Psychophysics*, *77*(8), 2562-2569.