Determining the latent structure of inhibitory control:

A two-study factor analysis of inhibition tasks

Supplemental Material

Exclusions and Data Cleaning, Study 1

Our Study 1 initial sample consisted of 180 participants with complete data. Our first exclusion criterion excluded participants for intentional premature responding (i.e., "clicking through" to finish the study sooner), defined as making 50 or more responses under 100ms in the course of completing all tasks and/or making 30 or more responses under 100ms within any of those individual tasks (n=17). Our second exclusion criterion for participants with complete data excluded participants for failing to follow task instructions, defined as making errors on over half the congruent trials within any conflict task and/or failing to maintain at least 70% accuracy in indicating the arrow direction in the stop signal task (n=6). Finally, research assistants blind to study hypotheses manually inspected the remaining participants' raw data files for haphazard responding (e.g., strings of very fast responses using the same response key); n=3 participants were identified as responding haphazardly, and these participants were thus excluded. These exclusion criteria resulted in a final sample of 154 participants for analysis.

Using all 180 Study 1 participants (i.e., not excluding any Study 1 participants) did not alter the primary conclusion: Inhibition task performance was better described by two factors than by a single factor. In particular, a one-factor solution was a marginally unacceptable fit to the data, $\chi^2(14) = 22.59$, p=.07, whereas a two-factor solution was an acceptable fit to the data, $\chi^2(8) = 10.19$, p=.25, and a marginally better fit to the data than the one-factor solution, $\Delta\chi^2(6) = 12.40$, p=.05.

Exclusions and Data Cleaning, Study 2

Our Study 2 initial sample consisted of 328 participants with complete data. Our first exclusion criterion excluded participants for intentional premature responding (i.e., "clicking through" to finish the study sooner), defined as making 50 or more responses under 100ms in the course of completing all tasks and/or making 30 or more responses under 100ms within any of those individual tasks (*n*=28). Our second exclusion criterion for participants with complete data excluded participants for failing to follow task instructions, defined as making errors on over half the congruent trials within any conflict task and/or failing to maintain at least 70% accuracy in indicating the arrow direction in the stop signal task (*n*=15). Finally, research assistants blind to study hypotheses manually inspected the remaining participants' raw data files for haphazard responding (e.g., strings of very fast responses using the same response key); *n*=6 participants were identified as responding haphazardly, and these participants were thus excluded. These exclusion criteria resulted in a final sample of 279 participants for analysis.

Using all 328 Study 2 participants (i.e., not excluding any Study 2 participants) did not alter the primary conclusion: Inhibition task performance was better described by two factors than by a single factor. In particular, a one-factor solution was an unacceptable fit to the data, $\chi^2(54) = 103.98$, $p<.001$, whereas a two-factor solution was a marginally acceptable fit to the data, $\chi^2(43) = 56.18$, $p=.09$, and a significantly better fit to the data than the one-factor solution, $\Delta\chi^2[9] = 47.80$, $p<.001$.

Descriptive Statistics for Study Variables

Study 1

Variable	*N*	Mean	*SD*	Min.	Max.	Skew	Kurtosis
Corsi Span	154	7.10	1.34	2	10	-0.2	1.71
Digit Span	154	7.16	1.41	2	10	-0.83	1.78
Go/No-Go Errs. of Commission	154	16.28	8.49	2	41	0.6	-0.11
SART Errors of Commission	154	11.27	6	0	26	0.32	-0.42
Simon Interference RT Effect	154	49.25	19.65	-0.11	97.29	0.1	-0.57

Stop-Signal Reaction Time	154	215.04	66.37	26.71	447.46	0.47	1.15
Stroop Interference RT Effect	154	151.07	75.24	8.83	341.65	0.3	-0.71

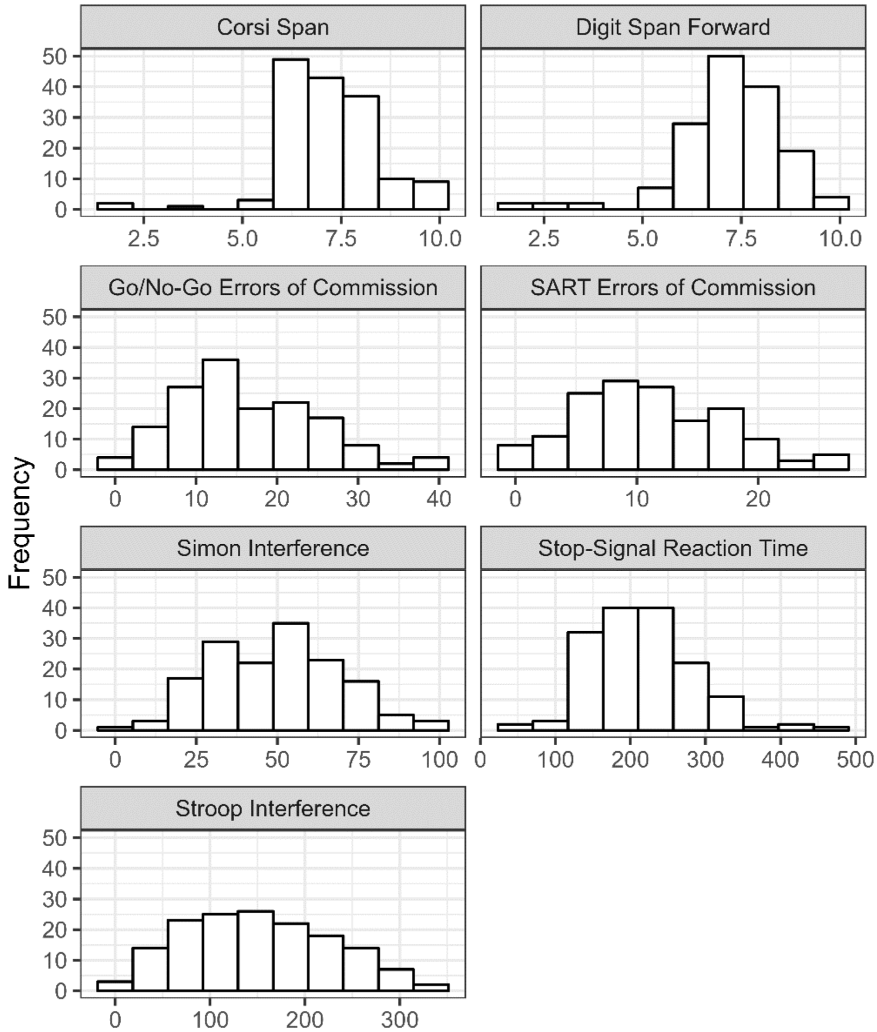


Figure S1. Distributions of each Study 1 task outcome.

Study 2

Variable	*N*	Mean	*SD*	Min.	Max.	Skew	Kurtosis
Corsi Span	279	7.24	1.17	2	10	-0.25	1.8
d2 Time Controlling Acc.	279	0.03	0.95	-3.98	2.59	-0.65	1.78
Digit Span	279	7.14	1.44	2	11	-0.87	2.3
Emot. Ster. Interfere. RT Effect	279	22.82	93.46	-286.94	321.83	0.07	0.83
Flanker RT Interference Effect	279	57.18	25.18	-16.94	142.12	0.62	1.04
Go/No-Go Errs. of Commission	279	18.33	8.83	1	43	0.43	-0.5
SART Errors of Commission	279	11.91	6.07	0	25	0.23	-0.93

Simon Interference RT Effect	279	44.22	25.78	-31.87	136.9	0.2	0.71
Simple RT	279	376.16	43.89	283.38	505.59	0.79	0.2
Stop-Signal Reaction Time	279	216.38	69.12	10.42	530.08	0.28	2.21
Stroop Interference RT Effect	279	80.8	68.82	-16.28	334.33	1.02	0.62
Vigilance Errors of Omission	279	2.77	2.23	0	9	0.73	-0.09

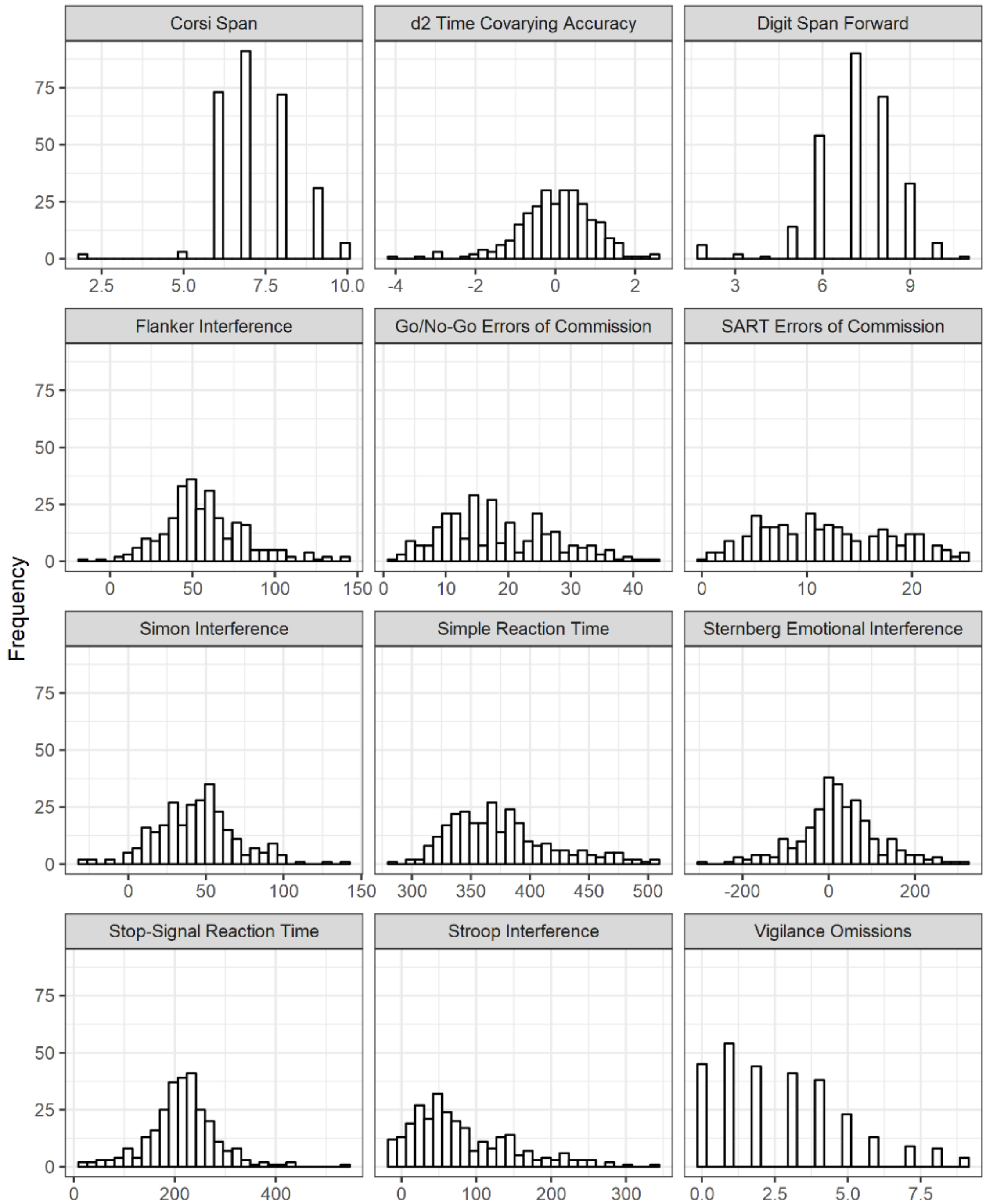


Figure S2. Distributions of the primary outcome from each cognitive task examined Study 2.

Analyses on Normality-Corrected Variables

We next attempted to determine whether any skewness or other nonnormality contributed to our results by conducting analyses on normality-corrected variables. To transform variables to a normal distribution, we used the bestNormalize package in R. We conducted two sets of transformations. First, using the bestNormalize() function with the allow_orderNorm argument set to false and both Lambert W arguments set to true in order to automatically transform each variable into the distribution that most approximates a normal distribution for that specific variable using more typical transformations (i.e., arcsinh(x), Box-Cox, center+scale, exp(x), Lambert W × F, log10(x+a), sqrt(x+a), Yeo-Johnson) according to the Pearson P test for normality. Second, using the orderNorm() function—which quantile ranks each variable according to a normal distribution and thus guarantees a normal distribution in the absence of ties—after adding a small amount of random noise (i.e., +rnorm(nrow(dat),0,0.0001)) to remove ties from the data (noise was not added to the first transformation analyses).

These analyses did not change any result indicating that separate factors of response inhibition and information gating were needed to account for the data. In particular, for the transformations excluding orderNorm, both Study 1 and Study 2 were better fit by a two-factor solution than a one-factor solution, p=.015, and p<.001, respectively, with loadings similar to the main text—indicative of response inhibition and information gating factors. Similarly, using the orderNorm function, both Study 1 and Study 2 were better fit by a two-factor solution than a one-factor solution, p=.016, and p<.001, respectively, with loadings similar to the main text—indicative of response inhibition and information gating factors. Interestingly, using the orderNorm transformation alone, Study 2 (but not Study 1) was better fit by a three-factor solution than a two-factor solution, p=.015; this third factor was indicated almost exclusively by digit span and Corsi span, with the other two factors consisting of response inhibition and information gating. Thus, one out of four combinations of transformations and studies suggested the separation of working memory storage from information gating. In short, results from transformed variable analyses were entirely consistent with the idea that response inhibition is a separate construct from information gating, but inconsistent evidence suggested that working memory storage may require a third factor to account for the data.

Study 1 Additional Analyses

We next attempted to determine the relative fits of a one-factor and a two-factor model to these data using confirmatory factor analysis, which removes cross-loadings between factors that are present in exploratory factor analyses. As in the exploratory factor analysis, a one-factor model was a poor fit to the data, $\chi^2(14) = 23.71$, $p = .050$, CFI = .697, RMSEA = .067, BIC = 3093.3, SABIC = 3049.0, AIC = 3050.8, whereas an uncorrelated two-factor model with a response inhibition factor (indicated only by go/no-go commissions, SART commissions, and stop-signal reaction time) and an information gating factor (indicated only by Stroop interference effects, Simon interference effects, digit span forward, and Corsi span) was an excellent fit to the data, $\chi^2(14) = 13.16$, $p = .514$, CFI = 1.000, RMSEA = .000, BIC = 3082.8, SABIC = 3038.5, AIC = 3040.3. Because these two models were nonnested and had equivalent degrees of freedom, they could not be compared via likelihood ratio test, but by all metrics ($\Delta\chi^2(0) = -10.55$, ΔBIC = -10.6, ΔSABIC = -10.6, ΔAIC = -10.6) the two-factor model was a notably better fit to the data. Figure S3 depicts this two-factor model and its loadings.

Figure S3. Confirmatory factor analysis for Study 1. This model was an excellent fit to the data, and all depicted loadings were significant.

Consideration of Outcome Type as an Explanation

Next, we examined whether our data were better explained by outcome type (i.e., response time vs. accuracy) than inhibition. To test this, we created a latent factor for accuracy—indicated by go/no-go commissions, SART commissions, forward digit span, and forward Corsi span—as well as a latent factor for response speed—indicated by Stroop RT effects, Simon RT effects, and stop signal RT. This model was a poor fit to the data, $\chi^2(13) = 23.37$, $p = .037$, CFI = 0.677, RMSEA = .072, BIC = 3098.0, SABIC = 3050.6, AIC = 3052.5. Comparing this model to the two-factor inhibition model described above (i.e., shown in Figure S3) is not possible via likelihood ratio test because these two models are not nested. Nonetheless, by all metrics, the two-inhibition-factor model was a notably better fit to the data than the two-outcome-factor model, $\Delta\chi^2(1) = -10.21$, ΔBIC = -15.3, ΔSABIC = -12.1, ΔAIC = -12.2.

Finally, we examined whether accounting for outcome type resulted in an acceptable three-factor model—response speed, accuracy, and a single inhibition factor—or whether the fit of a four-factor model—response speed, accuracy, response inhibition, information gating—was better than the two-factor inhibition model described above (shown in Figure S3). However, these three- and four-factor models were not identifiable. Therefore, the best model for these data fit inhibition via two latent factors.

Study 2 Additional Analyses

Exploratory Factor Analysis

An exploratory factor analysis of 12 tasks potentially loading on inhibitory control was conducted using the primary outcome measures from each of these tasks. A one-factor solution was a very poor fit to the data, $\chi^2(54) = 101.71$, $p < .001$, whereas a two-factor solution provided a good fit to the data, $\chi^2(43) = 46.31$, $p = .337$. A three-factor solution did not significantly improve model fit over the two-factor solution, $\Delta\chi^2(10) = 15.87$, $p = .103$, nor did a four-factor solution ($\Delta\chi^2[19] = 27.40$, $p = .096$), five-factor solution ($\Delta\chi^2[27] = 38.50$, $p = .070$), six-factor solution ($\Delta\chi^2[34] = 41.73$, $p = .170$), or seven-factor solution ($\Delta\chi^2[40] = 44.45$, $p = .256$). Importantly, because a two-factor solution provided a satisfactory fit to the data, no additional factors are required to explain the latent structure of these data, nor did any additional factors significantly improve the fit of the EFA to these data. This entails that task outcomes sometimes argued to rely on additional or other cognitive processes—such as the forward span tasks, simple reaction time task, or emotional interference task—did not require and would not benefit from additional factors (e.g., a working memory factor, or a processing speed factor) to explain their performance; instead, performance on these tasks at a latent level was satisfactorily explained with reference only to these two latent factors. Presumably, however, if additional tasks of these kinds (e.g., additional forward span tasks) had been included, then additional factors would have been necessary to explain the data. Scree plots and SABIC values are shown in Figure S4.

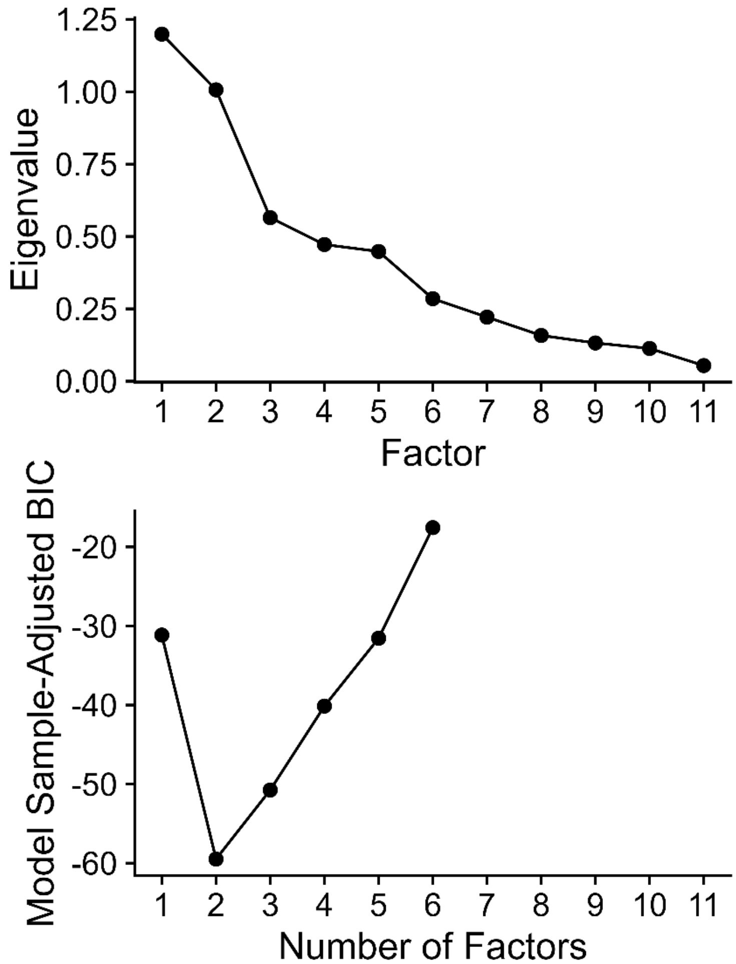


Figure S4. Eigenvalues for factors from factor analysis with all possible factors estimated, and SABIC values for factor solutions. SABIC could not be computed for more than seven factors given the number of variables included. The two-factor solution was preferred by the SABIC and χ^2 analyses.

Loadings from the exploratory factor analysis are presented in Table S3. In brief, the loadings on the first factor indicated a response inhibition factor, with go/no-go errors of commission and SART errors of commission displaying the largest loadings. The loadings on the second factor indicated an information gating factor, with Simon RT interference effects, Stroop RT interference effects, and reaction time displaying the largest loadings. Of note, the Stroop task loaded on both factors, but it displayed an inverse loading on the response inhibition factor, indicating that larger Stroop RT interference effects were associated with better response inhibition.

Table S3

Exploratory Factor Analysis Loadings for Each Task

	Factor 1: Response Inhibition	Factor 2: Info. Gating
Go/No-Go (# Errors of Commission)	**.67**	-.05
Sustained Attention to Response Task (# Errors of Commission)	**.58**	-.08
Stop Signal Task (Stop Signal Reaction Time)	**.26**	**.16**
Vigilance Task (# Errors of Omission)	**.19**	**.19**
Stroop Task (Interference Effect, RT)	**-.21**	**.46**
Simon Task (Interference Effect, RT)	.04	**.40**
Simple Reaction Time Test (RT)	.03	**.38**
d2 Test of Attention (Time Covarying Accuracy)	-.02	**.26**
Emotional Sternberg Task (Emotional Interference Effect, RT)	-.02	**.25**
Digit Span (Forward Span)	-.09	**-.21**
Corsi Block (Forward Span)	-.11	**-.17**
Flanker Task (Interference Effect, RT)	.14	.00

Note: Loadings that were significant in the confirmatory factor analysis are shown in bold. Factors were rotated using varimax rotation, but identical primary loadings with approximately equal loading values were obtained without rotation or with promax and oblimin rotations.

We also conducted sensitivity analyses to determine whether a two-factor solution was required only because of the commonality between the sustained attention to response task and the go/no-go. In this, we excluded either one of the aforementioned tasks and conducted the exploratory factor analysis on the remaining tasks. When the SART was excluded, a one-factor was a poor fit to the data, $\chi^2(44) = 69.24$, $p = .008$, whereas a two-factor solution was an acceptable fit to the data, $\chi^2(34) = 42.89$, $p = .141$. Similarly, when excluding the go/no-go, a one-factor solution was a poor fit to the data, $\chi^2(44) = 63.77$, $p = .027$, whereas a two-factor solution was an acceptable fit, $\chi^2(34) = 39.52$, $p = .237$. Therefore, the reason that the data were best fit by a two-factor solution was not that the commonality between the SART and go/no-go required a second factor; excluding either of those two tasks still required a two-factor solution to fit the data.[1]

Initial Confirmatory Factor Analysis

Prior to the confirmatory factor analysis presented in the main text, we first constructed a CFA from the loadings in the EFA, presented above. Indicators of each factor were those with an EFA loading of $> \pm .118$, as this was the smallest correlation our study could detect as significant given our sample size. However, EFA loadings differ from CFA loadings due to a lack of cross-loadings, entailing that some EFA loadings of $> .118$ were no longer significant in the CFA. Nonsignificant paths were removed from this CFA, thus trimming flanker interference effects—which did not significantly load on either latent factor—and the correlation between response inhibition and information gating. The model was an excellent fit to the data, $\chi^2(41) = 39.16$, $p = .553$, CFI = 1.000, RMSEA = .000, BIC = 8713.7, SABIC = 8634.4, AIC = 8622.9. The model indicated that response inhibition and information gating are distinct at a latent level: The correlation between response inhibition and information gating was nonsignificant, $r < .01$, $p = .957$, and fixing it to zero did not worsen the fit of the model (BIC = 8713.7) compared to a model that estimated the correlation ($\chi^2[40] = 39.15$, $p = .508$, CFI = 1.000, RMSEA = .000, BIC = 8719.3, SABIC = 8636.9, AIC = 8624.9), $|\Delta\chi^2|(1) = 0.00$, $p = .957$, ΔBIC = -5.6, ΔSABIC = -2.5, ΔAIC = -2.0. The resulting model is presented in Figure S5.

[1] When excluding the 104 participants with emotional interference effects < 0 (leaving n=175), a one-factor solution was still an unacceptable fit to the data, $\chi^2(54) = 95.13$, $p < .001$, whereas a two-factor solution was an acceptable fit to the data, $\chi^2(43) = 51.24$, $p = .182$. Similarly, removing Sternberg emotional interference from the factor analysis entirely did not alter these results: a one-factor solution was still an unacceptable fit to the data, $\chi^2(44) = 88.38$, $p < .001$, whereas a two-factor solution was an acceptable fit to the data, $\chi^2(34) = 40.23$, $p = .214$

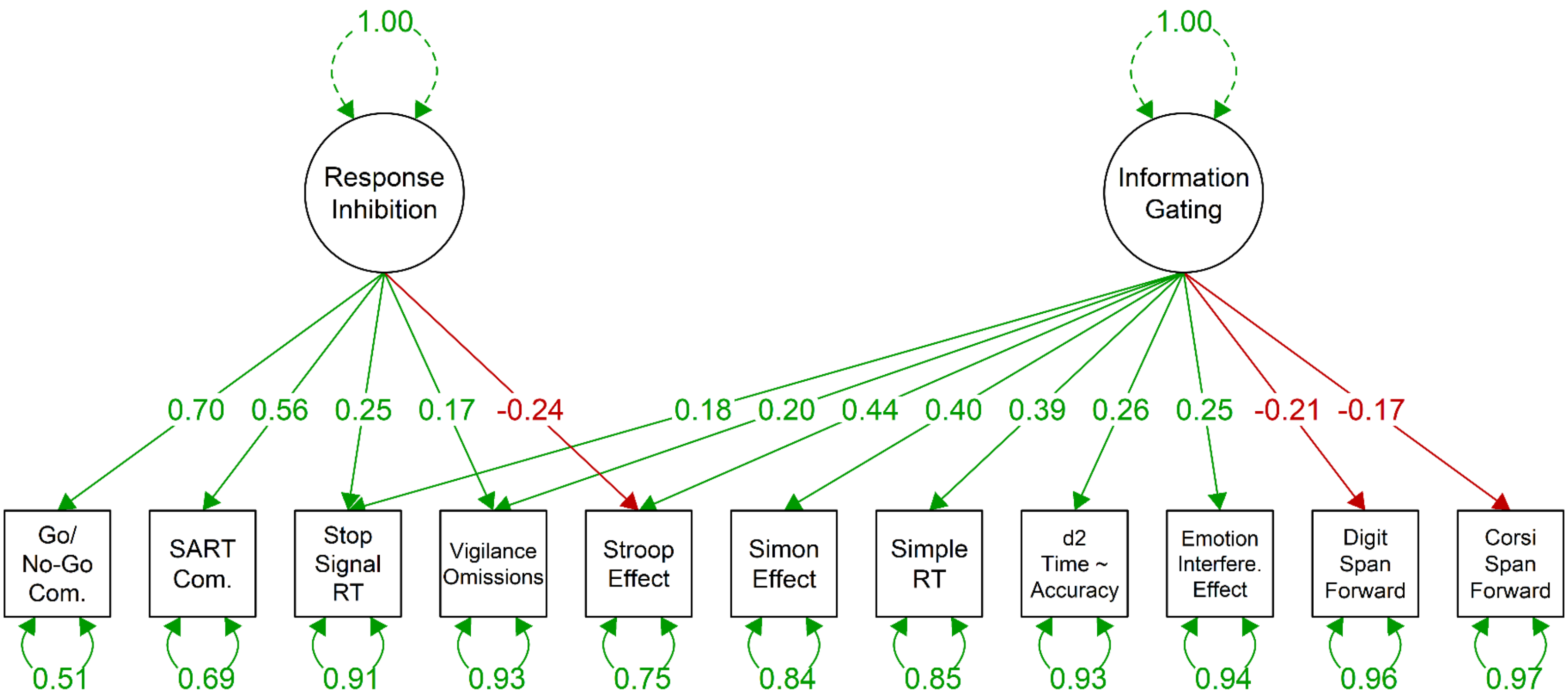


Figure S5. Structural equation model derived from trimming nonsignificant paths from the exploratory factor analysis. The model was an excellent fit to the data. The correlation between response inhibition and information gating (not depicted) was nonsignificant, $r < .01$, $p = .957$, and fixing it to zero—as shown here—did not worsen model fit, $|\Delta\chi^2|(1) = 0.003$, $p = .957$ (and by some metrics, it improved model fit, $\Delta BIC = -5.6$). Both digit span forward and Corsi span are coded such that higher scores indicate better performance, whereas the rest of the tasks' outcomes are coded such that higher scores indicate worse performance (e.g., greater interference or more errors).

As shown in Figure S5, some of the variables in the initial CFA loaded onto both response inhibition and information gating (i.e., the stop-signal task and the vigilance task loaded onto both factors in the same direction, and the Stroop task loaded onto both factors in opposite directions). Therefore, in order to determine if response inhibition and information gating were separable without any shared loadings, we estimated the model with each task loading onto only its strongest factor. This was the first CFA presented in the main text. This main-text CFA model was a worse fit by most metrics than the above model with some shared indicators (Figure S3),

$|\Delta\chi^2|(2) = 9.64$, $p = .008$, ΔBIC = -1.6, ΔSABIC = 4.8, ΔAIC = 5.7. The analyses presented here were moved for space considerations in the manuscript.

Comparison with the Unity Model of Executive Functions

The primary difference between the best fitting model to our tasks and the unity model of executive functions is that the unity model of executive functions views response inhibition as equivalent to the common executive function (e.g., goal-directed information gating and/or amplification) at a latent level; indeed, in the unity model, inhibition is no different from the common executive function supporting performance on all executive function tasks in the unity model. Therefore, we compared a model with a single inhibition factor (i.e., the unity model) being indicated by all of the tasks with our two-factor model described above (shown in Figure S5). In this analysis, we found that the two-factor model (fit statistics provided above) was a significantly better fit than the unity model ($\chi^2[44] = 93.31$, $p < .001$, CFI = .550, RMSEA = .063, BIC = 8751.0, SABIC = 8681.2, AIC = 8671.1), $|\Delta\chi^2|(3) = 54.15$, $p < .001$, ΔBIC = -37.3, ΔSABIC = -46.8, ΔAIC = -48.2. Crucially, however, exploratory analyses revealed that when both of the tasks that selectively loaded on the response inhibition factor in the best-fitting model—the go/no-go and the SART—were removed from the model, the two-factor model ($\chi^2[25] = 31.64$, $p = .169$, CFI = .870, RMSEA = .031, BIC = 7174.1, SABIC = 7109.0, AIC = 7100.7) did not significantly differ from the unity model ($\chi^2[27] = 34.86$, $p = .143$, CFI = .846, RMSEA = .032, BIC = 7166.0, SABIC = 7110.7, AIC = 7101.5), $|\Delta\chi^2|(2) = 3.22$, $p = .200$, ΔBIC = 8.0, ΔSABIC = 1.7, ΔAIC = 0.8. This indicates that without including variables that selectively load on response inhibition (e.g., errors of commission on the go/no-go or SART), structural equation models examining the latent structure of inhibitory control may be unable to detect response inhibition as a latent factor distinct from information gating.[2]

Restriction of Variables

Because many of the tasks used in this study may be controversial with respect to their utilization of inhibitory control, we ran analyses including only go/no-go commissions, SART commissions, stop-signal reaction time, Stroop interference, Simon interference, and emotional Sternberg interference. As in the above analyses, in exploratory factor analyses, a single factor was a poor fit to the data, $\chi^2(9) = 29.27$, $p < .001$, whereas a two-factor solution was a sufficiently good fit to the data, $\chi^2(4) = 2.29$, $p = .683$, and improved model fit relative to the one-factor solution, $\Delta\chi^2(5) = 26.99$, $p<.001$; a three-factor solution could not be compared to the two-factor solution due to insufficient degrees of freedom in the three-factor solution. Confirmatory factor analyses are presented in the main text. Loadings of the two-factor solution for the EFA are as follows:

Table S4

Exploratory Factor Analysis Loadings for Restricted Variables EFA

	Factor 1: Response Inhibition	Factor 2: Info. Gating
Go/No-Go (# Errors of Commission)	**.67**	-.08
Sustained Attention to Response Task (# Errors of Commission)	**.58**	-.10
Stop Signal Task (Stop Signal Reaction Time)	**.28**	.14
Stroop Task (Interference Effect, RT)	-.16	**.60**
Simon Task (Interference Effect, RT)	.06	**.37**
Emotional Sternberg Task (Emotional Interference Effect, RT)	.01	**.29**

Note: Loadings that were significant in the confirmatory factor analysis are shown in bold. Factors were rotated using varimax rotation, but identical primary loadings with approximately equal loading values were obtained without rotation or with promax and oblimin rotations.

[2] An additional exploratory factor analysis also found that when both the go/no-go and SART were excluded, a one-factor solution was an acceptable fit to the data, $\chi^2(35) = 45.07$, $p = .118$. These results further support the idea that including either the go/no-go or the SART is necessary for detecting a response inhibition factor in factor analysis.

Consideration of Outcome Type as an Explanation

We first examined whether including latent variables indicated by outcomes of specific types (i.e., reaction time or accuracy-based outcomes) improved model fit. The latent variable for accuracy outcomes was indicated by go/no-go commissions, SART commissions, vigilance omissions, digit span, and Corsi span, whereas the latent variable for time-based outcomes was indicated by stop-signal reaction time, Simon interference RT effects, Stroop interference RT effects, simple RT, Sternberg emotional interference effects, and d2 time controlling accuracy (results did not differ d2 time controlling accuracy indicated accuracy as well, nor did results differ if this variable was removed from models entirely). In contrast to Study 1, a four-factor model with two outcome-indicated latent variables (accuracy, time-based) and two inhibition latent variables was a better fit to the data ($\chi^2[30] = 12.49$, $p = .998$, CFI = 1.000, RMSEA = .000, BIC = 8749.0, SABIC = 8634.8, AIC = 8618.3) than the two-factor inhibition model (shown in Figure S5; fit statistics provided above) by some metrics, $\Delta\chi^2(11) = 26.66$, $p = .005$, ΔAIC = -4.6, but not by others, ΔBIC = 35.3, ΔSABIC = 0.4. We examined whether this may have been because of a secondary outlet for the covariance between Corsi and digit span (the latent accuracy variable, present in the outcome-indicated model) not present in the two-factor inhibition model. Once the covariance between Corsi span and digit span was specified in both models, the two-factor inhibition model ($\chi^2[40] = 29.43$, $p = .891$, CFI = 1.000, RMSEA = .000, BIC = 8709.6, SABIC = 8627.2, AIC = 8615.2) was a better fit than the four-factor outcome type and inhibition model ($\chi^2[29] = 15.62$, $p = .980$, CFI = 1.000, RMSEA = .000, BIC = 8757.7, SABIC = 8640.4, AIC = 8623.4) by all indices, $\Delta\chi^2(11) = 13.81$, $p = .244$, ΔBIC = -48.1, ΔSABIC = -13.3, ΔAIC = -8.2. Similarly, when digit span and Corsi span were omitted from both models, the two-factor inhibition model (χ^2[24] = 17.44, p = .829, CFI = 1.000, RMSEA = .000, BIC = 7116.4, SABIC = 7049.9, AIC = 7040.2) was a better fit than the four-factor outcome type and inhibition model (χ^2[15] = 7.07, p = .956, CFI = 1.000, RMSEA = .000, BIC = 7156.8, SABIC = 7061.6, AIC = 7047.8) by all indices, $\Delta\chi^2(9)$ = 10.37, p = .322, ΔBIC = -40.4, ΔSABIC = -11.8, ΔAIC = -7.6. Therefore, adding latent factors for outcome type did not improve model fit over a two-factor inhibition-only model once the covariance between Corsi span and digit span was equated between models.

More importantly, we examined whether a two-factor outcome type model (indicators for each outcome type described in the paragraph above) without an inhibition factor (χ^2[43] = 67.55, p = .010, CFI = 0.776, RMSEA = .045, BIC = 8730.8, SABIC = 8657.9 AIC = 8647.3) fit the data better than either the model shown in Figure S5 or the model shown in Figure 2. Because this model was not nested with either the Figure S5 model or the Figure 2 model, we do not provide p values for these model comparisons, but by every metric, the two-factor outcome-type-only model was a worse fit than either two-factor inhibition model: versus the model shown in Figure S5, $\Delta\chi^2(2)$ = 28.40, ΔBIC = 17.1, ΔSABIC = 23.5, ΔAIC = 24.4, and versus the model shown in Figure 2, $\Delta\chi^2(0)$ = 18.76, ΔBIC = 18.8, ΔSABIC = 18.8, ΔAIC = 18.8. Results did not differ when the covariance between latent accuracy and latent RT was constrained to zero, nor did they differ, importantly, when the residual covariance between Corsi span and digit span was included in the outcome type model.

Next, we examined whether a three-factor model—with two outcome type factors (accuracy and time-based; indicators described above) and a single inhibition factor (indicated by all variables)—fit the data better than the models above. This model (χ^2[31] = 26.90, p = .677, CFI = 1.000, RMSEA = .000, BIC = 8757.8, SABIC = 8646.8 AIC = 8630.7) looked like a response inhibition model, rather than a common executive function model: Only go/no-go commissions, SART commissions, and stop-signal reaction time loaded significantly onto the inhibition factor (loadings for Stroop, Simon, etc., were nonsignificant, *p*s>.160). More importantly, this model was a worse fit than the model shown in Figure S5 by all metrics suitable for comparing nonnested models, $\Delta\chi^2(-10) = -12.2$, ΔBIC = 44.1, ΔSABIC = 12.3, ΔAIC = 7.7, and it was a worse fit than the model shown in Figure 2 by all metrics suitable for comparing nonnested models, $\Delta\chi^2(-12) = -21.90$, ΔBIC = 45.7, ΔSABIC = 7.6, ΔAIC = 2.1. Most importantly, this three-factor model was a substantially worse fit by every metric than the nonnested four-factor model described above (i.e., with two outcome type factors and two inhibition factors), $\Delta\chi^2(2) = 17.52$, ΔAIC = 13.5, ΔBIC = 6.3, ΔSABIC = 12.6, showing that two inhibition factors are critical even when outcome type is controlled.

Study 2 Supplemental Discussion

Discussion of the above is as follows.

Some unexpected and notable task loadings merit discussion. In particular, although vigilance task errors of omission primarily loaded onto the information gating factor and stop-signal reaction time (SSRT) primarily loaded onto the response inhibition factor, as expected, the significant secondary loadings of both of these task outcomes onto the other inhibition factor may seem somewhat surprising (Stroop RT interference effects are discussed in the next paragraph). However, the characteristics of these tasks make these secondary loadings easily interpretable. In the vigilance task used in this study, there were very long waiting periods (up to 15 seconds) that required attention to a potential target that appeared for only a very brief period of time (25 milliseconds). Thus, in addition to the primary demands the vigilance task made on information gating, eyeblinks and saccades were automatic, prepotent actions that needed to be inhibited for successful performance on this task, as one blink or saccade could cause a participant to miss a presented target (Caffier et al., 2003; Johns et al., 2009). Although speculative, the need to inhibit eyeblinks and saccades—or to overtly look in the direction of any possible distraction—could explain the secondary loading of vigilance omissions on the response inhibition factor. As for SSRTs from the stop signal task, SSRTs require including reaction time in calculation of SSRTs in order to estimate the time required to inhibit an activated response (Verbruggen et al., 2013; Verbruggen & Logan, 2009). Because reaction time requires information gating—indeed, simple reaction time loaded on the information gating factor in this study—the inclusion of reaction time in the method of calculating SSRT likely contributed to the secondary loading of this outcome on information gating. Importantly, though, the model estimating response inhibition and information gating as distinct latent executive functions was still an acceptable fit to the data when both of these variables had their secondary loadings fixed to zero. Therefore, although the secondary loadings of these variables were interesting, they are explainable, and their existence does not alter any of the primary conclusions of the current study.

Alternate Analytic Approach

A reviewer recommended an alternative analytic approach, which we conducted at the second round of revisions. We believe that they were quite informative. We considered rewriting the manuscript main text results using the following, but we ultimately decided that it would be better to include this information in the supplement at this stage, and reference it as appropriate in the discussion and use it to better contextualize and understand our ambiguous results.

These analyses approached our outcome data from a different perspective, where each task outcome was governed by both speed and response. Justification for this scoring is provided in the subsequent section.

In particular, for each task, we divided proportion correct (i.e., accuracy) on (when possible, inhibition-related or difficult) trials by mean response time in seconds on (when possible, inhibition-unrelated or easy) correct trials. Higher scores thus represent better accuracy than would be expected for the speed of responding, and thus helps to control for decision boundary and speed-accuracy tradeoffs. So, for example: Stroop Outcome = Mean Accuracy on Incongruent Trials / Mean RT on Correct, Congruent Trials. Similarly: Go/No-Go Outcome = Mean Accuracy on No-Go Trials / Mean RT on Correct, Go Trials.

- This strategy directly translates between Stroop, Simon, flanker, emotional Sternberg (negative as difficult/inhibition, neutral as easy/noninhibition), go/no-go, and SART.
- For the digit and Corsi span tasks, we computed sum of total digits and squares correctly recalled across all trials, and divided those sums by mean RT on the first third of participants' trials (i.e., in low-load trials).
- For the vigilance task, we used accuracy on go (target) trials (as omissions were the primary outcome of interest) divided by reaction time on go trials; using total accuracy did not change any of the inferences or primary loadings described below (though the loading values changed slightly).
- For d2, we divided mean trial accuracy ((hits – misses + correct rejects – false alarms)/(hits + misses + correct rejects + false alarms)) by mean trial RT.
- For simple reaction time, we divided mean accuracy ((hits – misses – premature responses)/(hits + misses + premature responses)) by mean RT to hits.

- For the stop-signal task, we used stop-signal reaction time and multiplied it by -1 so that higher values represented better performance, as in the other outcomes.

Therefore, although the Stroop, Simon, flanker, emotional Sternberg, go/no-go, and SART are most similar, the basic strategy works for all tasks with outcomes that did not already combine response time and accuracy (i.e., those besides SSRT). We then reanalyzed our data. The results, described below, are much stronger and more compelling for our primary inference: more than a common executive function is needed to explain inhibitory control data.

The bivariate correlation matrices for each study are as follows:

Study 1:

	Simon	Stroop	Corsi	Digit	Stop Sig.	G/N-G
Simon						
Stroop	.58***					
Corsi	.25**	.11				
Digit	.14	.12	.16			
Stop Signal	.15	.17*	-.02	.00		
Go/No-Go	.33***	.31***	.05	.06	.22**	
SART	.24**	.24**	.06	-.03	.30***	.24**

Study 2:

	Simon	Stroop	Flanker	Sternberg	Corsi	Digit	Smpl RT	Vigilance	d2	Stop Sig.	G/N-G
Simon											
Stroop	.61***										
Flanker	.41***	.41***									
Sternberg	.32***	.39***	.30***								
Corsi	.21***	.27***	.17**	.16**							
Digit	.10	.12	.08	.19**	.30***						
Simple RT	.32***	.34***	.34***	.23***	.15*	.12					
Vigilance	.21***	.24***	.36***	.22***	.02	.02	.27***				
d2	.22***	.24***	.21***	.28***	.13*	.14*	.21***	.09			
Stop Signal	.29***	.22***	.15*	.19**	.08	-.00	.09	.04	.11		
Go/No-Go	.27***	.11	.19**	.05	.03	-.03	.14*	.15*	.06	.21***	
SART	.28***	.12*	.23***	.12*	.08	.06	.17**	.05	.10	.23***	.40***

The exploratory factor analyses for each study are as follows:

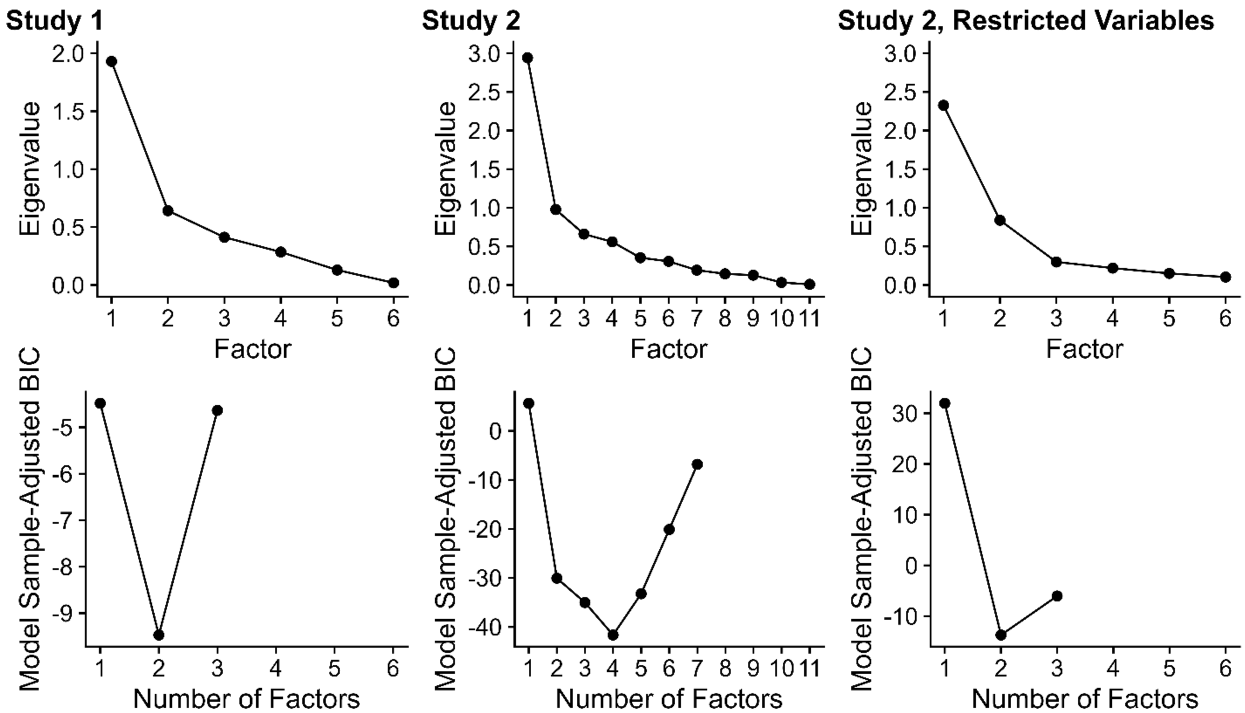


Figure S6.

Study 1 required two factors to explain the data, as in the primary analyses: one-factor $\chi^2(14)=21.08$, $p=.0996$, two-factor $\chi^2(8)=5.14$, $p=.743$, $\Delta\chi^2(6)=15.94$, $p=.014$. Three factors did not improve the Study 1 EFA fit, as in primary analyses: three-factor $\chi^2(3)=0.84$, $p=.840$, $\Delta\chi^2(5)=4.30$, $p=.508$.

When all variables were included in Study 2, Study 2 required and was preferred by four three factors by χ^2 (one-factor $\chi^2[54]=137.52$, $p<.001$; two-factor $\chi^2[43]=74.97$, $p=.002$; three-factor $\chi^2[33]=45.57$, $p=.071$; four-factor $\chi^2[24]=16.97$, $p=.850$), and the fit to the data was not improved by both either χ^2 (four- to five-factor comparison, $\Delta\chi^2[8]=11.12$, $p=.195$) and SABIC (see Figure S6) by adding a fifth factor.

When the variables in Study 2 were restricted to those that were least controversial (i.e., go/no-go, SART, stop-signal, Stroop, flanker, emotional Sternberg, and Simon), which were also the variables most comparable in adjusting for RT in outcomes, only two factors were required and preferred by both χ^2 (one-factor $\chi^2[14]=66.41$, $p<.001$, two-factor $\chi^2(8)=5.96$, $p=.651$,

$\Delta\chi^2(6)=60.44$, $p<.001$; three-factor $\chi^2[3]=1.34$, $p=.718$, $\Delta\chi^2[5]=4.62$, $p=.464$) and SABIC (see Figure S6). The factor loadings (using varimax rotation) for these outcomes are as follows, with primary (i.e., strongest) loadings highlighted in bold:

Study 1

Variable	Factor 1	Factor 2	Uniqueness
Simon	**.84**	.30	.21
Stroop	**.56**	.35	.56
Corsi	**.29**	-.03	.91
Digit	**.15**	.02	.98
Stop-Signal RT	-.03	**.56**	.68
Go/No-Go	.25	**.43**	.75
SART	.10	**.52**	.72

Study 2

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Simon	**.69**	.32	.13	.11	.40
Stroop	**.82**	.05	.15	.14	.29
Flanker	**.41**	.24	.36	.12	.63
Emot. Stern.	**.38**	.08	.22	.27	.72
Corsi	.25	.02	-.01	**.42**	.76
Digit	.02	-.01	.04	**.66**	.57
Simple RT	**.34**	.13	.26	.19	.76
Vigilance	.15	.03	**.77**	-.01	.38
d2	**.26**	.07	.05	.23	.87
Stop-Signal RT	.27	**.31**	-.02	.01	.83
Go/No-Go	.08	**.62**	.14	-.06	.59
SART	.10	**.65**	.01	.11	.56

Study 2, Restricted Variables

Variable	Factor 1	Factor 2	Uniqueness
Simon	**.70**	.32	.40
Stroop	**.85**	.04	.28
Flanker	**.48**	.25	.71
Emot. Stern.	**.46**	.08	.79
Stop-Signal RT	.26	**.30**	.84
Go/No-Go	.09	**.61**	.62
SART	.12	**.64**	.57

Notably, in a structural equation model separating the restricted variables tasks into their primary factors, the model—which, after accounting for residual covariances, was a good fit to the data, $\chi^2(11)=18.50$, $p=.071$, CFI: 0.979, RMSEA: 0.049—accounted for the covariance between go/no-go and SART, indicating that this factor was not an artifact of similarity between the go/no-go and SART:

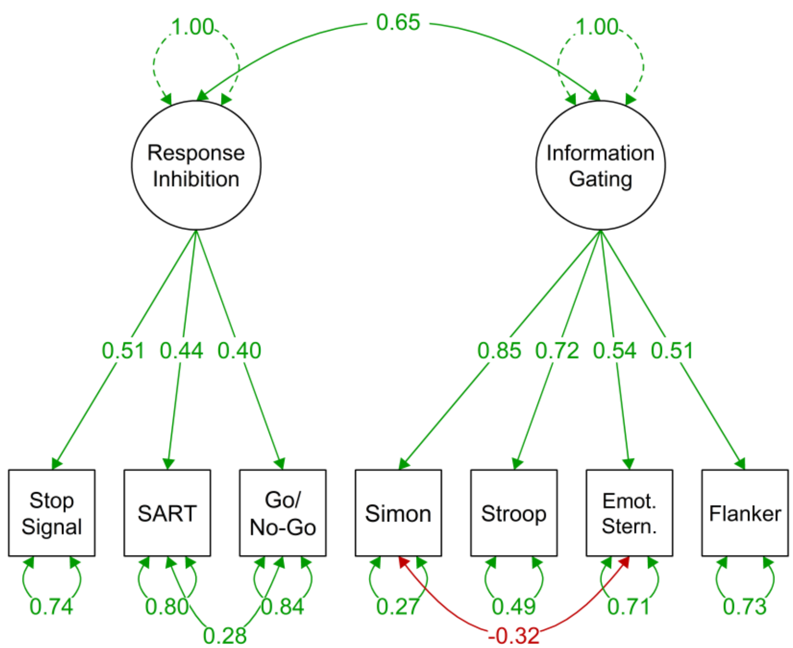


Figure S7. Restricted variables CFA in Study 2, loading onto their primary factor. All variables are coded such that higher values = better performance. All estimated paths were significant.

In the combined multi-group two-study SEM analyses, an uncorrelated two-factor model was a poor fit to the data ($\chi^2[47]=115.29$, $p<.001$, CFI=0.825, RMSEA=.083), but Study 1's exploratory factor analysis using this new scoring method suggested some overlap between the Simon task and response inhibition, and it further suggested that many of the response inhibition variables loaded on the goal-directed information gating and/or amplification factor as well. Therefore, we allowed all paths to load on the information gating factor, similar to the common executive function model. We found that this model, with all latent and residual variances constrained to equality across studies, was a good fit to the data, $\chi^2(43)=50.64$, $p=.197$, CFI=0.980, RMSEA=.029. This two-study model is shown below:

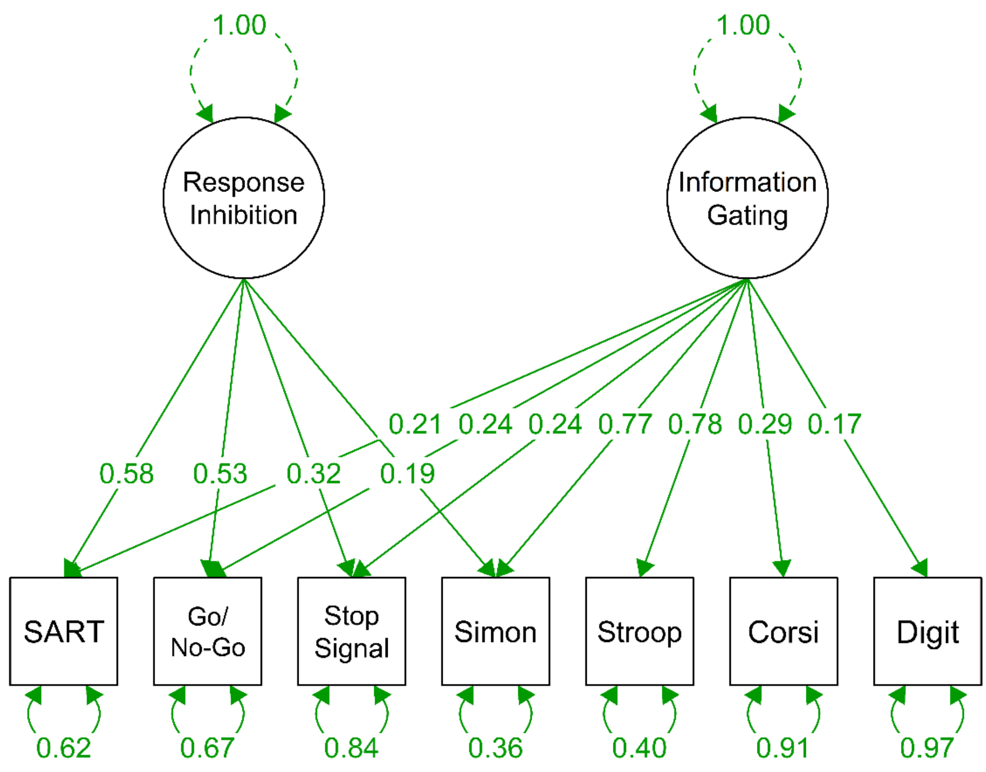


Figure S8. Multi-study model using the alternate task scoring approach. All variables are coded such that higher values indicate better performance. All estimated paths were significant.

Additionally, Study 2's EFA suggested that digit and Corsi shared unique variance, so we fit a multi-group two-study confirmatory factor analysis akin to the unity model, with working memory maintenance as its own factor. This model, with all latent and residual variances constrained to equality across studies, was an excellent fit to the data, $\chi^2(40)=29.99$, $p=.875$, CFI=1.00, RMSEA<.001, though its smallest eigenvalue was near-zero. This two-study model is shown below:

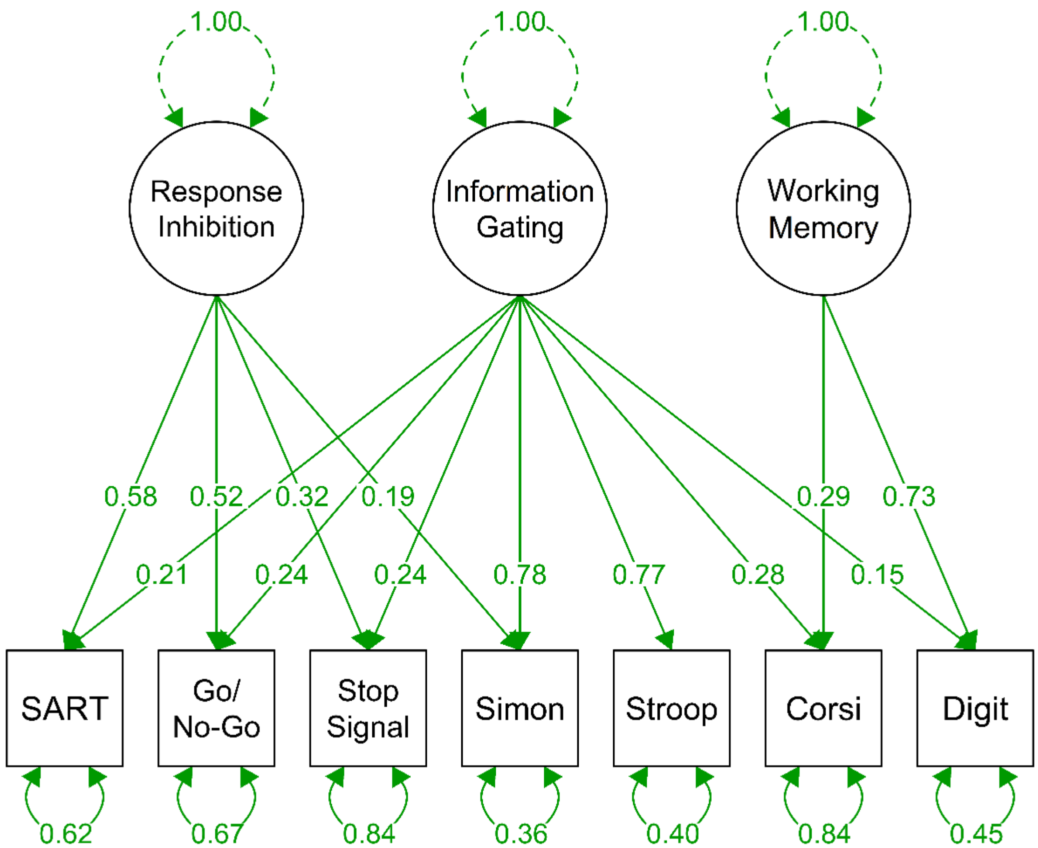


Figure S9. Multi-study model using the alternate task scoring approach. All variables are coded such that higher values indicate better performance. All estimated paths were significant.

Together, these analyses strongly suggest that response inhibition is a distinct control process from what we are referring to as goal-directed information gating and/or amplification, which we believe is likely to be Miyake and Friedman's common executive function.

Justification for Alternate Task Scoring

The ratio between inhibitory trial (e.g., no-go) accuracy and noninhibitory trial (e.g., go) mean RT has been validated and used as a measure of inhibitory control that adjusts for speed-accuracy tradeoffs in a number of studies within fMRI and cognitive neuroscience literature (e.g., Cascio et al., 2022; Dotterer et al., 2021; Garcia-Egan et al., 2019; Gonzalez Alarm et al., 2023; Hinton et al., 2018; Hirose et al., 2012; Tomlinson et al., 2020; Tompson et al., 2020). The studies that have taken this approach have largely used go/no-go tasks, given that go/no-go tasks cannot compute a RT difference score nor correct for speed-accuracy tradeoffs without this mixing-conditions approach—correct no-go trials have no response speed. It is for this reason that we used the measure we did: No other measure that adjusts for outcome type works well across all tasks most frequently taken to index inhibitory control via some outcome (i.e., go/no-go, Simon, Stroop, SART, etc.).

The general rationale for this approach nonetheless applies well to conflict tasks (e.g., Simon) or other, similar tasks: The general rationale is that response speed can be quantified well when trials do not require inhibition, response inhibition accuracy can be best indexed in trial accuracy when trials require inhibition of an incorrect response, and taking the ratio of these variables can provide an index of inhibitory control accuracy or general response speed that adjusts for the other (e.g., Tompson et al., 2020).

For ease of understanding the remainder of this section, we refer to the measure we used as the "cross-domain inhibition efficiency" score (CDIE).

Because no study to date has compared the properties of this—or, to our knowledge, any—integrated speed-accuracy measure (i.e., the CDIE) within the context of a conflict task (i.e., one with incongruent and congruent trials), we conducted a simulation study to this end. We simulated trials and participants using the Diffusion Model for Conflict tasks (DMC; Ulrich et al., 2015), which is a domain-general model developed to fit all tasks containing trials requiring inhibition and trials not requiring inhibition (e.g., congruent and incongruent trials). This model characterizes empirical performance data well across a variety of tasks and produces patterns of results that are characteristic of inhibition tasks (e.g., negative-going delta functions) that standard diffusion models cannot (Ulrich et al., 2015).

We randomly sampled parameters from feasible ranges for each parameter. Each parameter's feasible range was determined by reported parameter values fit to empirical data by Ulrich et al. (2015) and Shields et al. (2019; 2020). In particular, for decision boundary, we sampled values between 40 and 80 in a uniform distribution. For the interference gamma function, we set the scale parameter at 2 as recommended (White et al., 2018), we randomly drew amplitude from a uniform distribution from 10 to 30, and we randomly drew peak onset latency from a uniform distribution from 60 to 150. Finally, we randomly drew goal-directed drift rate from a uniform distribution from .15 to .7. Mean nondecision time was set to 300 and the standard deviation of nondecision time was set to 30. We simulated 300 trials per participant (150 congruent, 150 incongruent). We simulated 10,000 participants with feasible parameters (3,000,000 simulated trials).

Decision boundary is the parameter that quantifies the speed-accuracy tradeoff in this model (Ulrich et al., 2015). We quantified inhibitory control as the mean difference between the two drift functions (i.e., goal-directed and interference; more formally, mean of $\mu_C - \mu_A$ across t) from the 0^{th} to the 60^{th} percentile of the cumulative distribution of the interference gamma function. We conducted sensitivity analyses using different t windows for quantifying inhibitory control via this difference; none of our conclusions below differed across these sensitivity analyses.

After simulating these data, we compared the balanced integrated scores (BIS), inverse efficiency scores (IES), and CDIE in relation to decision boundary and inhibitory control. Because our simulated task had both incongruent and congruent trial types, BIS was computed at the simulated participant level (using participant-level RT means and proportions correct) using the formulas given by Liesefeld and Janczyk (2023):

$$BIS_{i,\ congruent} = \frac{PC_{i,\ congruent} - \overline{PC}}{S^{PC}} - \frac{\overline{RT}_{i,\ congruent} - \overline{\overline{RT}}}{S^{\overline{RT}}}$$

$$BIS_{i,\ incongruent} = \frac{PC_{i,\ incongruent} - \overline{PC}}{S^{PC}} - \frac{\overline{RT}_{i,\ incongruent} - \overline{\overline{RT}}}{S^{\overline{RT}}}$$

$$BIS_{i,\ inhibition} = BIS_{i,\ incongruent} - BIS_{i,\ congruent}$$

Where $PC_{i,j}$ = proportion correct for participant *i* in trial condition *j*, $\overline{PC}$ = grand mean proportion correct across all participants and conditions, S^{PC} = standard deviation of proportion correct across all participants and trial conditions, $\overline{RT}_{i,j}$ = mean response time for participant *i* in trial condition *j*, $\overline{\overline{RT}}$ = grand mean RT across all participants and conditions, and , $S^{\overline{RT}}$ = standard deviation of mean response time for all participants and trial conditions.

Although BIS typically includes all trial conditions, we also calculated BIS in a second way, where $BIS_{congruent}$ or $BIS_{incongruent}$ were only z-scored via the current condition (i.e., not across both conditions, as is typical, but only using congruent scores for $BIS_{congruent}$, and only using incongruent scores for $BIS_{incongruent}$). We refer to the standard calculation of BIS in our $BIS_{inhibition}$ score as $BIS_{inhibition\_1}$ and the variant BIS that only includes the one trial condition in calculation of each component within the $BIS_{inhibition}$ score as $BIS_{inhibition\_2}$.

We computed IES as

$$IES_{i,\ congruent} = \frac{\overline{RT}_{i,\ congruent}}{PC_{i,\ congruent}}$$

$$IES_{i,\ incongruent} = \frac{\overline{RT}_{i,\ incongruent}}{PC_{i,\ incongruent}}$$

$$IES_{i,\ inhibition} = IES_{i,\ incongruent} - IES_{i,\ congruent}$$

Finally, we computed the cross-domain inhibition efficiency (CDIE) score, as stated above, as

$$CDIE_{i} = \frac{PC_{i,\ incongruent}}{\overline{RT}_{i,\ congruent}}$$

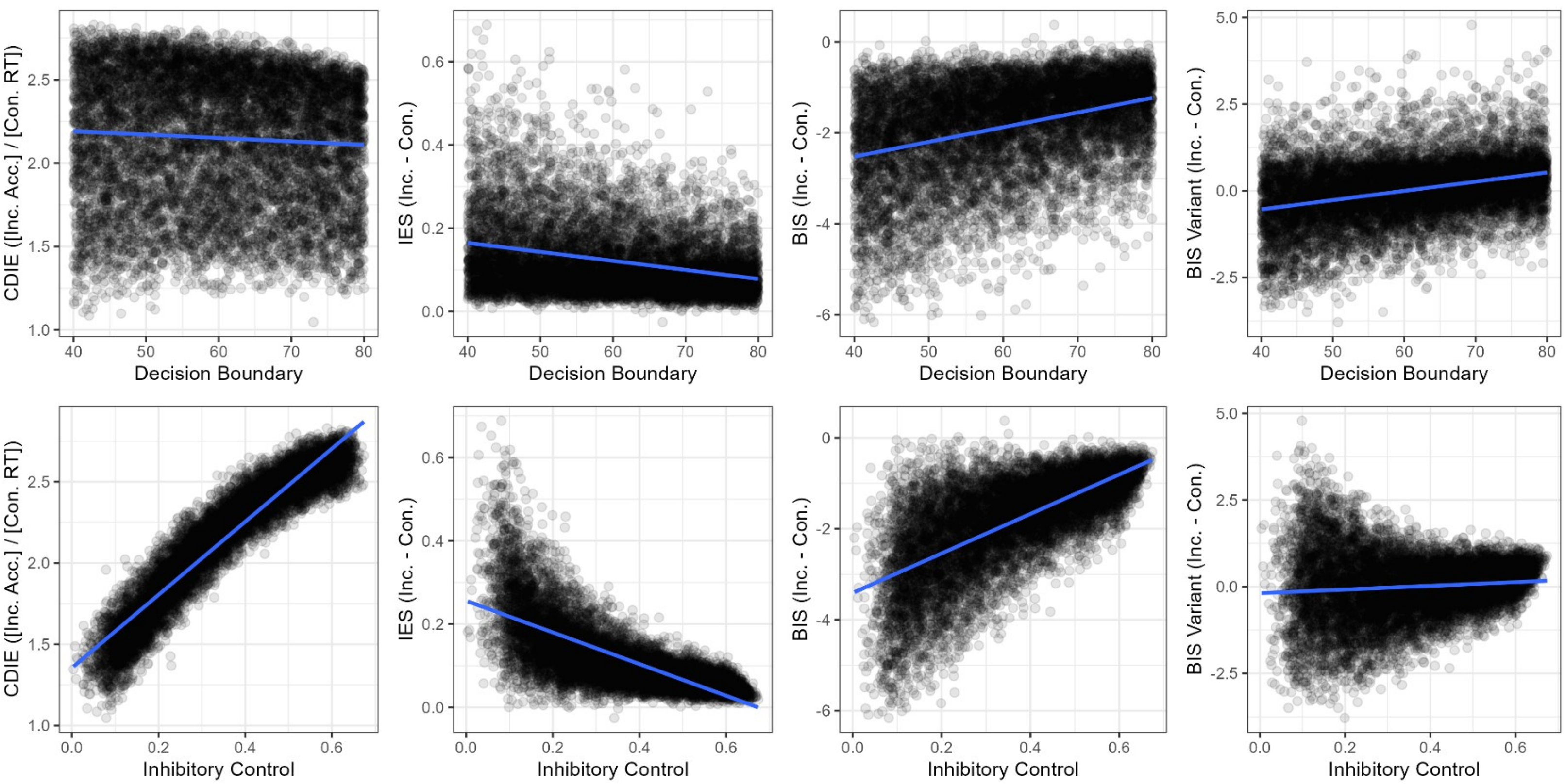
Due to 10,000 simulated participants, all of the following analyses were significant, and we therefore focus on the magnitudes of associations to compare amongst them. We consider an effect size to be meaningful when the correlation is at least small in magnitude (i.e., $|r| > .10$).

For BIS, we found that although these scores performed well in individual trial types (i.e., within congruent trials or incongruent trials), this was not the case when calculating an inhibitory control BIS with either method (i.e., using both j types congruent and incongruent when computing each type's BIS and then taking the difference of the two j types, referred to as $BIS_{inhibition\_1}$; or, using only the respective congruent or incongruent trial type when computing each type's BIS and then taking the difference of the two j types, referred to as $BIS_{inhibition\_2}$). In particular, both $BIS_{inhibition\_1}$ and $BIS_{inhibition\_2}$ were moderately strongly associated with decision boundary, $r = .352$, and, $r = .329$, respectively. Additionally, although $BIS_{inhibition\_1}$ was associated with control, $r = .665$, $BIS_{inhibition\_2}$ was not meaningfully associated with inhibitory control, $r = .092$.

Similarly, for IES, we found that although these scores performed well in individual trial types (i.e., within congruent trials or incongruent trials), this was not the case within an inhibition IES. In particular, the inhibition IES ($IES_{incongruent} - IES_{congruent}$) showed a moderately strong association with decision boundary, $r = -.285$. The inhibition IES showed a strong association with inhibitory control, $r = -.702$.

Most importantly, CDIE was not meaningfully associated with decision boundary, $r = -.061$, and, notably, CDIE was strongly correlated with inhibitory control, $r = .944$.

These results are shown in the figures below, with $BIS_{inhibition\_2}$ as "BIS Variant."



Because correct no-go trials do not have a response speed (and, faster responses on no-go trials index worse performance, not better), the inhibition forms of either the BIS and IES that are conceptually appropriate for conflict tasks such as Stroop or Simon are not appropriate for the go/no-go or SART. Because of this, we believe—especially in light of these simulation results—that the CDIE represents the only metric of inhibitory control usable across no-go and conflict tasks. Moreover, the CDIE has been predictively validated as an index of inhibitory control in neuroimaging studies, concurrently validated in our empirical data (i.e., given its stronger concurrent associations that also cluster more similarly to what would be expected from prior work than the raw scores), and construct validated in this new simulation (i.e., CDIE is associated with control, not decision boundary, when the two are experimentally manipulated).

We thus believe that the CDIE is appropriate for our use in the supplementary material as the second set of analyses examining whether outcome type might have explained our results, with its results converging with the alternative structural equation models suggesting that outcome types do not account for our results.

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