SUPPLEMENTAL MATERIAL

Diffusion Model Fitting Procedure

The diffusion model was fit to individual subject's data using maximum likelihood estimation implemented in fast-dm 30 (Voss, Voss, & Lerche, 2015). We conceptualized and fit 15 separate models of increasing complexity that varied in the locus of the PM intention. Specifically, we tested models which allowed PM intention to manifest on boundary separation, starting point, nondecision time or drift rate in isolation and then in combination up to and including PM influencing all four of the major parameters. Based on prior modeling work (Ratcliff, Gomez, & McKoon, 2004), stimulus type (i.e., words vs. nonwords) was modeled as a change in drift rate only. Finally, although we estimated the variability parameters, due to the relatively small number of trials we did not allow these parameters to vary as a function of either stimulus type or PM intention. The table below presents the summed AIC and BIC values for each model. As can be seen, the AIC model (bolded) allowed boundary separation, nondecision time, and starting point to vary across blocks, whereas the BIC model (bolded) only retained the boundary separation parameter.

Model	Varying by Block	K	∑AIC	∑BIC
1	а	9	38788	43010
2	$T_{\rm er}$	9	40180	44402
3	Z	9	43737	47959
4	v	10	42074	46757
5	a , $T_{\rm er}$	10	38338	43022
6	<i>a</i> , <i>z</i>	10	38468	43152
7	<i>a</i> , <i>v</i>	11	38651	43794
8	$T_{\rm er}, z$	10	39917	44601
9	$T_{\rm er}$, v	11	39441	44584
10	<i>Z</i> , <i>V</i>	11	41700	46843
11	$a, T_{\rm er}, z$	11	38034	43177
12	a , $T_{\rm er}$ v	12	38206	43807
13	a , z, v	12	38470	44071
14	T _{er,} z, v	12	39264	44865
15	a, T _{er,} z, v	13	38085	44142

Model Fits for AIC Selected Model

Model fits for each condition and age group are displayed below. These figures plot the observed (circles and standard error bars) accuracy, correct RT quantiles (.1, .5 and .9), and median error RT against those predicted by the best-fitting model parameters (triangles). As shown, the model generally recovers the data to within one standard error.





We have chosen to present model fit graphically as quantitative measures of goodness of fit can be heavily influenced by the number of trials and lead to either always reject the model (due to a large number of trials) or missing gross levels of misfit (due to small numbers of trials. Thus, graphical presentation remains one of the best ways to convey model fit (Voss, Voss, & Lerche, 2015).

Variability Parameters for AIC Selected Model

Although we had no a priori reason to expect differences in variability parameters, we include the analyses here. The three measures were submitted to a 2 (age: young, old) x 2 (condition: PMI, OTI) between-subjects ANOVA.

Drift Rate Variability. Variability was greater for young adults, F(1,121) = 4.47, p = .037, $\eta_p^2 = .037$. However, there was no effect of condition, and no age x condition interaction, F's < 2.40, p's > .123.

Nondecision Time Variability. This analysis revealed no significant effects, F's < 1.

Starting Point Variability. Variability was greater for young adults, F(1,121) = 7.02, p = .009, $\eta_p^2 = .055$. However, there was no effect of condition, and no age x condition interaction, F's < 1.

Boundary Separation Analysis for BIC Selected Model

Boundary separation cost was greater for older adults, F(1,121) = 13.62, p < .001, $\eta_p^2 = .101$, and in the PMI condition, F(1,121) = 8.57, p = .004, $\eta_p^2 = .066$. The age x condition interaction was not significant, F < 1. Thus, the results for boundary separation for the BIC selected model are identical to the AIC selected model.

References

- Ratcliff, R., Gomez, P., & McKoon, G. (2004). A diffusion model account of the lexical decision task. *Psychological Review*, 111(1), 159.
- Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analyses: a tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*, 336.