DRIFTING THROUGH THE NOISE

A diffusion model analysis of the interrelation of storage and updating in working memory

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Theoretical Background

Working memory (WM) is understood to be a cognitive system that allows for temporary storage as well as concurrent processing of information, providing support for mental work and coherent thought (Baddeley, 2012). The Central Executive is the least well understood component of the Baddeley model of WM, and is thought to be responsible for attentional control mechanisms, i.e. Executive Functions like updating, inhibition and task-shifting (Miyake et al., 2001). However, cognitive tasks that are employed to measure WM-capacity (like variations of n-back) usually confound storage- and processing-demands.

To dissociate these aspects of WM, we have designed a paradigm in which storage- (e.g., memory set size) and processing-demands (e.g., memory updating) can be separately manipulated.

To further assess their interrelation, we have conducted a diffusion model (DM) analysis (Ratcliff & McKoon, 2008; Fig. 1), as the quality of representations in WM may relate to the signal-to-noise ratio of the evidence accumulation.

The Ratcliff Diffusion Model

The DM mathematically models dichotomous decisions. It uses individual distributions of accuracies (Acc) and reaction times (RT) to estimate the underlying decisional processes. Thus the reaction is seperated in four invariant parameters, each representing a different functional aspect of the reaction.

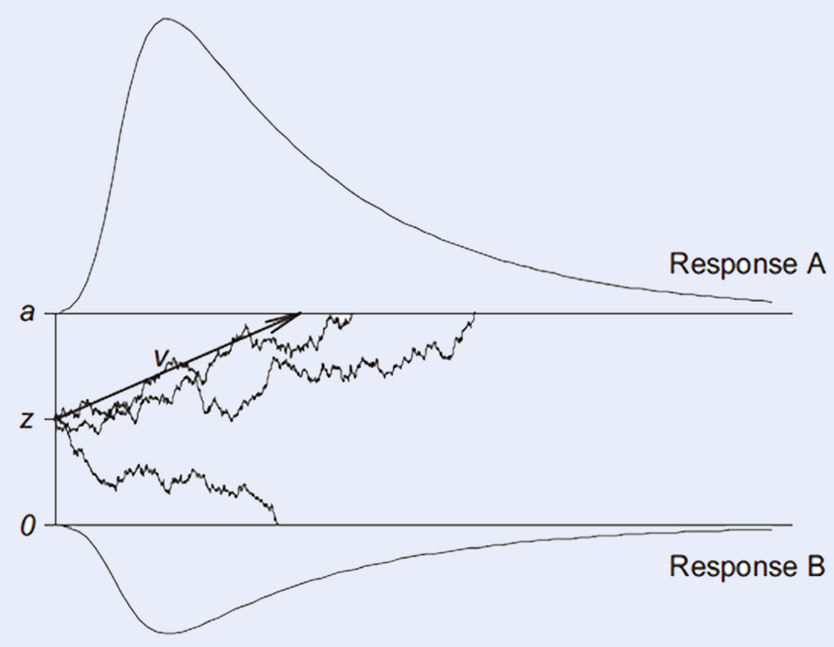


Fig. 1: A visual representation of evidence accumulation in the Ratcliff DM

Parameters

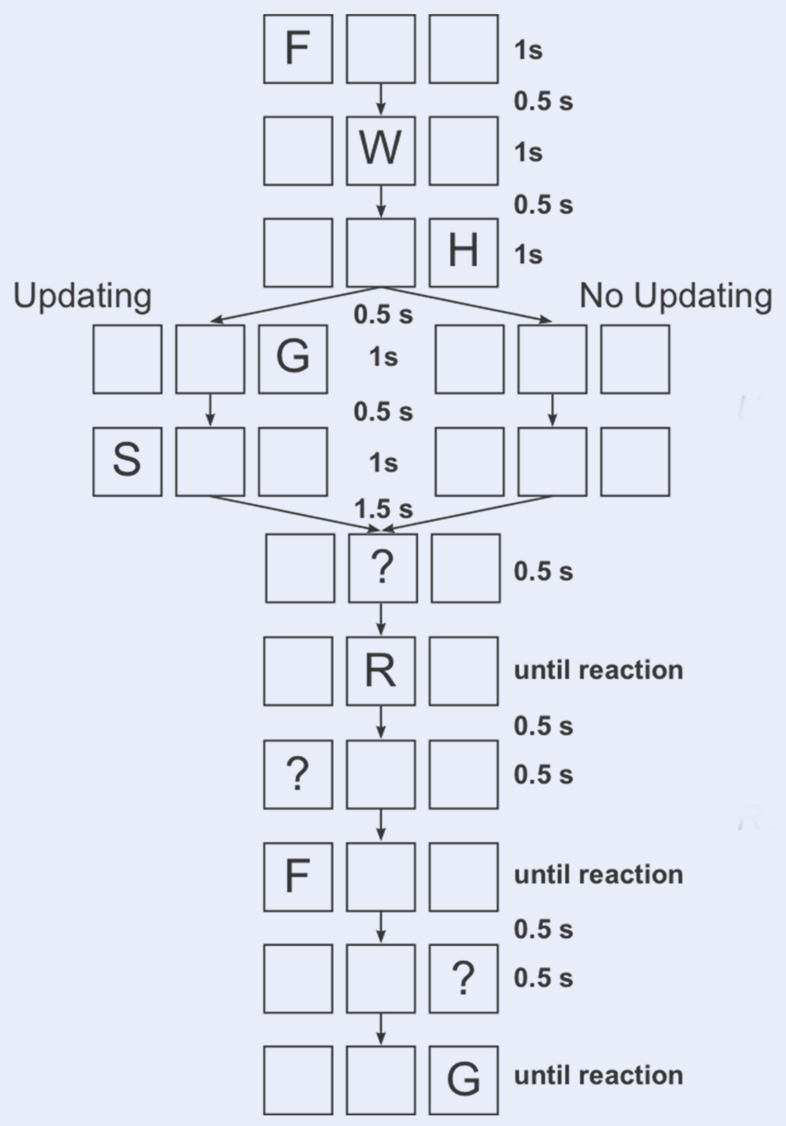
Drift Rate v : Mean rate of information accumulation, signal to noise ratio

Threshold Separation a : Decisional threshold

Non-Decisional time t_0 : Encoding, response execution

Decisional Bias z : Shift of the accumulation-starting-point towards response A or B

Experimental Paradigm



1. Encoding Phase:
Random consonants appear serially in each of the 3 to 5 boxes. Encode letter and position. No letter duplicates within each trial.

2. Updating Phase
(In the updating condition) two new letters were presented at two randomly selected positions. Replace them in your mental set.

3. Retrieval Phase
After a short cue (i.e., a question mark) probe letters were presented in each box. The order of retrieval was random for each trial. Participants had to decide as quickly and as accuracetely as possible whether the probe letter matched the letter they remebered at the respective position.

Diffusion Modelling

Four different models were estimated with fast-dm30 (Voss , Voss & Lerche, 2015) in a model comparison approach to identify the best fitting model.

I. Baseline Model - fixed parameters
II. Restricted Model (v) - only v varied
III. Restricted Model (a) - only a varied
IV. Full Model - a, t_0, v varied (fixed z)

See Table 1. for Model-Fit comparison. Model II was selected for all further anaylsis due to superior fit.

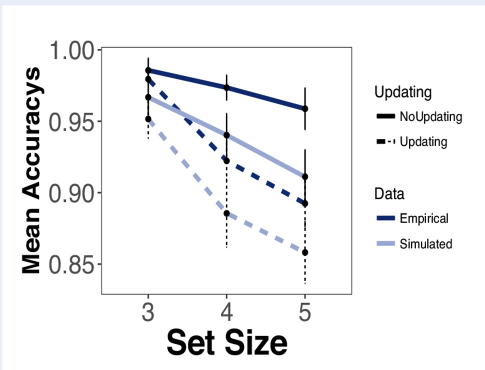
Table 1. Model-Fit according to Akaike and Baysian Information Criteria. a difference of > 10 for AIC & BIC was interpreted as better model fit.

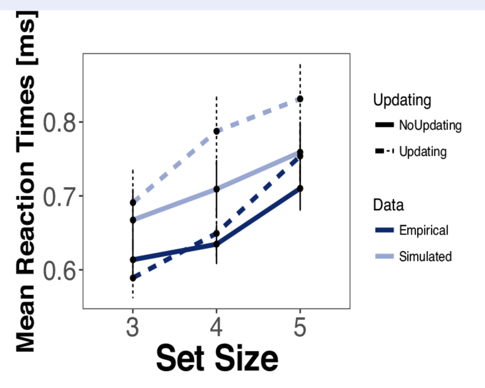
	AIC	BIC	ΔAIC	ΔBIC
Baseline Model	174.61	201.60	38.25	28.50
Restricted Model (*v*)	136.36	176.10	0	0
Restricted Model (*a*)	164.86	201.60	28.50	25.50
Full Model (a, t_0, v)	140.71	218.8	***4.35***	42.80

Out of Sample Prediction (OSP)

To further validate the the drift parameter as a measure of performance in WM tasks, we conducted an OSP with construct-samples from the fast-dm30 package.

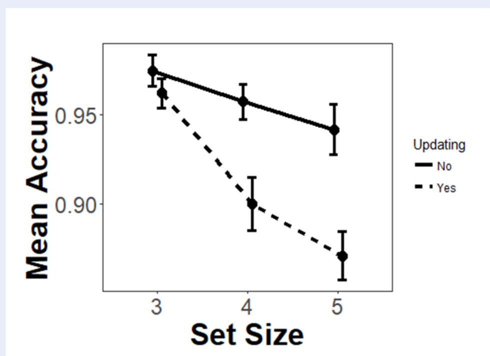
An odd-even split was applied, model data was estimated from the even half and tested on its predictive power for the odd half of the emprical distribution of RT and Acc. See Figures to the right for comparison of empirical and simulated data. Effects of the Updating and Set Size conditions could be predicted suffiently.





Results

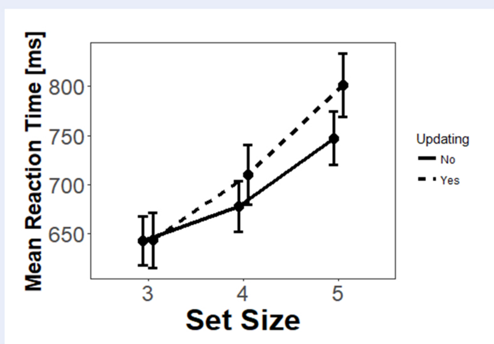
(Student sample; $N = 39$; Mean Age = 22.79; SD = 5.52; 60.5 % female)



ME Set Size : $F(2, 76) = 33.13$, $\varepsilon = 0.847$ $\omega^2 = .35$, $p < .0001$

MEUpdating $F(1, 38) = 33.40$, $\omega^2 = .29$, $p < .0001$

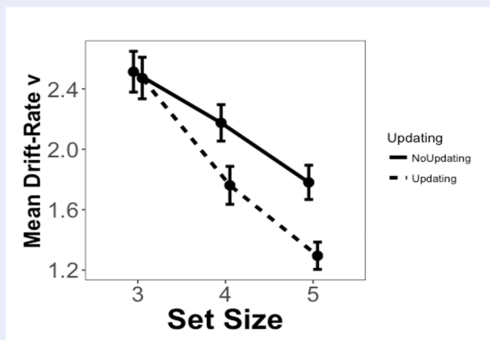
IE SSxUpd $F(2, 76) = 15.74$, $\varepsilon = 0.920$, $\omega^2 = .11$, $p = .0002$



ME Set Size : $F(2, 76) = 74.34$, $\varepsilon = 0.902$, $\omega^2 = .56$, $p < .0001$

ME Updating $F(1, 38) = 4.10$, $\omega^2 = .04$, $p < .0001$

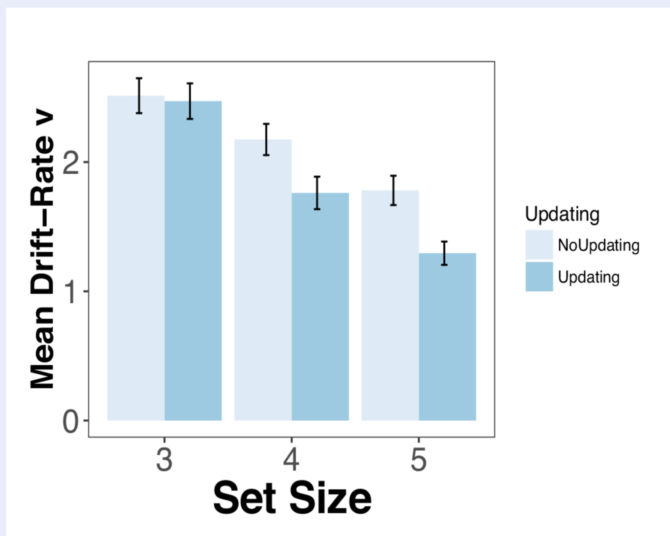
IE SSxUpd $F(2, 76) = 5.26$, $\varepsilon = 0.884$, $\omega^2 = .04$, $p = .0002$



ME Set Size : $F(2, 76) = 89.54$, $\varepsilon = 0.825$, $\omega^2 = .60$, $p < .0001$

ME Updating $F(1, 38) = 25.99$, $\omega^2 = .24$, $p < .0001$

IE SSxUpd $F(2, 76) = 10.68$, $\varepsilon = 0.903$, $\omega^2 = .08$, $p = .0002$



Drift rates decreased with increasing Set Size

SS 4: $t(38) = 4.83$, $p < .0001$, $d = .77$
SS 5: $t(38) = 5.68$, $p < .0001$, $d = .91$

Drift rates decreased with increasing Set Size x Updating

SS 3 vs. SS 4 No Updating: $t(38) = 3.85$, $p = .0003$, $d = .62$
SS 3 vs. SS 4 Updating: $t(38) = 8.06$, $p < .0001$, $d = 1.29$

SS 4 vs. SS 5 No Updating: $t(38) = 4.73$, $p < .0001$, $d = .72$
SS 4 vs. SS 5 Updating: $t(38) = 5.30$, $p < .0001$, $d = .85$

Take Home Messages

1. **Working memory updating and storage share a common cognitive resource which limits working memory capacity.**

2. **There is preliminary evidence that the mean rate of decisional evidence accumulation (i.e., *v*) is a good singular predictor for working memory performance.**

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REFERENCES

Baddeley, A. (2012). Working memory theories, models, and controversies. *Annual review of psychology*, *63*(1), 1–29.

Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of experimental psychology*: General, *130*(4), 621-640.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural Computation*, *20*(4), 873-922.

Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analysis: a tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*, 336.