The Association Between Health and Component Decision Processes

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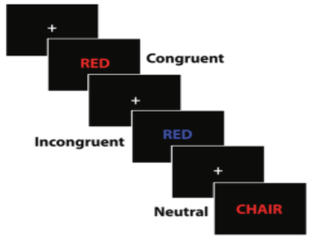
Background & Hypothesis

Reduced physical health of the body is associated with poor executive function[1]. Yet it is unclear what underlying component mechanisms of decision control are associated with measures of physical health. Here we tested the hypothesis that individual variability in physical health of the body correlates with specific decision processes.

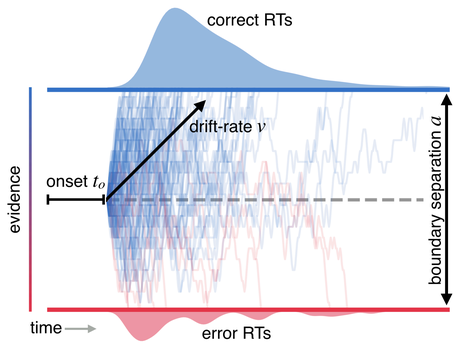
Methods

Participants: N=110 (24, male; mean age of 44.6 years) community dwelling adults were evaluated on several health measures; body mass index (BMI; mean BMI = 32.35 +/- .37), maximum volume of oxygen ($VO2_{Max}$; mean $VO2_{Max}$ = 22.86 +/- .005), and body fat composition using dual-energy x-ray absorptiometry (DXA; mean DXA = .42 +/- .005). In addition to these primary measures, a latent variable analysis (principle component analysis) was used to identify the lower dimensional components of shared variance across these health measures labeled as PC1 (r_{BMI}= .42, r_{V02max}= .78, r_{DXA}= .43) and PC2 (r_{BMI}= .78, r_{V02max}= .19, r_{DXA}= .007).

Task: Color-Word Stroop Task: Report the color of the letters, ignoring the words. Rapid event-related condition (N trials = 120)



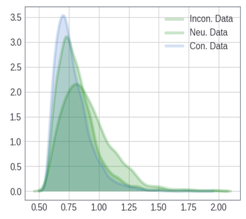
Drift Diffusion Model (DDM)



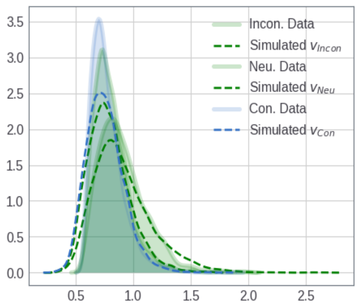
We fit individual subject choice data from the Stroop Task using a hierarchical drift diffusion model (HDDM)[2] fit to the reaction times (RT) and accuracies. We compared models in which either the drift-rate (v), onset time (t) threshold (a), or bias (z) was allowed to vary across levels of congruency.

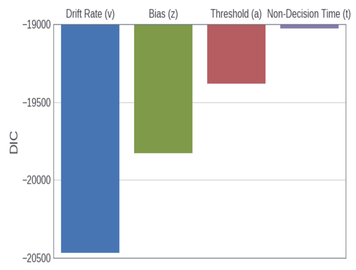
Stroop Effect

We find similar results to the stroop effect when examining reaction time (RT) distributions across conditions such that incongruent conditions are associated with the slowest RT while congruent conditions are associated with the fastest RT



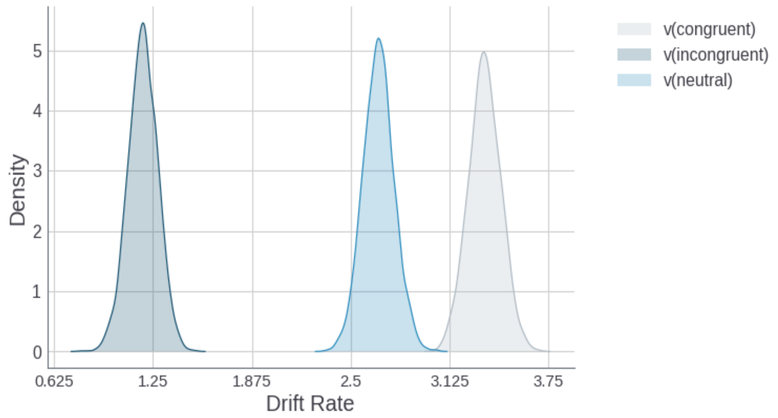
Model Fits





The simulated data from the parameter estimates overlaps with the behavioral data across conditions verifying the model

Using deviance information criterion (DIC), the best fit model to explain the condition effects on RT was the the model where the drift rate was modulated by level of congruency.



Consistent with the mean shifts in RTs, the posterior probabilities on the drift rates showed that the drift rate is substantially slower in the incongruent condition than the other two conditions and fastest in the congruent condition.

DDM associations with health factors

The relationship between health factors and DDM parameters was modeled using linear regression . Model subset selection was used to determine when to include control variables (age, years of education, sex) in a model. **After adjusting for multiple comparisons (Bonferroni), none of the health factors associated with any of the DDM parameters.**

Bayes Factor (BF_{01})

	BMI	DXA	VO2	PC1	PC2
$v_{Incon-Neu}$	3.99	7.54	3.02	8.99	.94
$v_{Con-Neu}$	8.82	10.23	4.39	4.56	10.25
a	10.48	9.96	7.97	10.48	9.22
z	7.22	9.97	8.54	10.45	5.03
t	5.59	6.11	10.37	9.58	5.50

In most models there was substantial ($3<BF_{01}<20$), but not strong ($BF_{01} > 20$), evidence in favor of supporting the null hypothesis that health does not associate with any of the DDM parameters.

Conclusions

Cue conflict was found to modify the drift rate of the decision process; however, a significant relationship between component decision processes and physical health measures was not identified.

References

1. Jarmolowicz D.P., D.D. Reed, F.D. DiGennaro Reed, et al. 2016. The Behavioral and Neuroeconomics of Reinforcer Pathologies: Implications for Managerial and Health Decision Making. Manage. Decis. Econ. 37: 274–293.

2. Wiecki TV, Sofer I and Frank MJ (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. Front. Neuroinform. 7:14. doi:10.3389/fninf.2013.00014

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