

Development of a neuroimaging paradigm to dissociate value, weighting, and attention in multi-attribute choice

Daniel J Wilson¹, Cendri Hutcherson¹

¹Department of Psychology, University of Toronto

// BACKGROUND

1. Decisions are often captured as a weighted sum over multiple attributes 1:

Summed Value = $w_1^*a_1 + w_2^*a_2 + ... + w_n^*a_n$

where a is how "good" the attribute is, and w how "important". 2. Good decisions require flexibly weighting attributes according to context or goals.

3. The neurocomputational processes enabling attribute evaluation and flexible weighting remain poorly understood.

4. Unclear how value and attention interact.

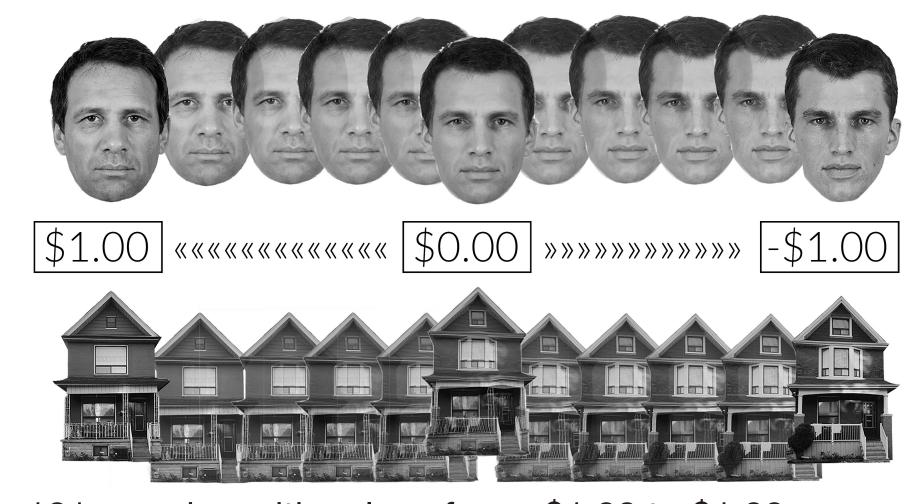
// GOALS

- 1. Develop fMRI and EEG-compatible paradigm for tracking value and attention during multi-attribute choice.
- 2. Investigate influence of flexible attribute weighting on attention.
- 3. Investigate influence of attention on attribute valuation and weighting.

// METHODS

- 1. Subjects (n=31) learned values from morphed pairs of images of houses and faces.
- 2. Subjects accepted or rejected a proposed combination of 2 attributes (1 face and 1 house) based on the summed value. Weights were applied to attributes on a trial-by-trial basis to affect importance.

Stimuli

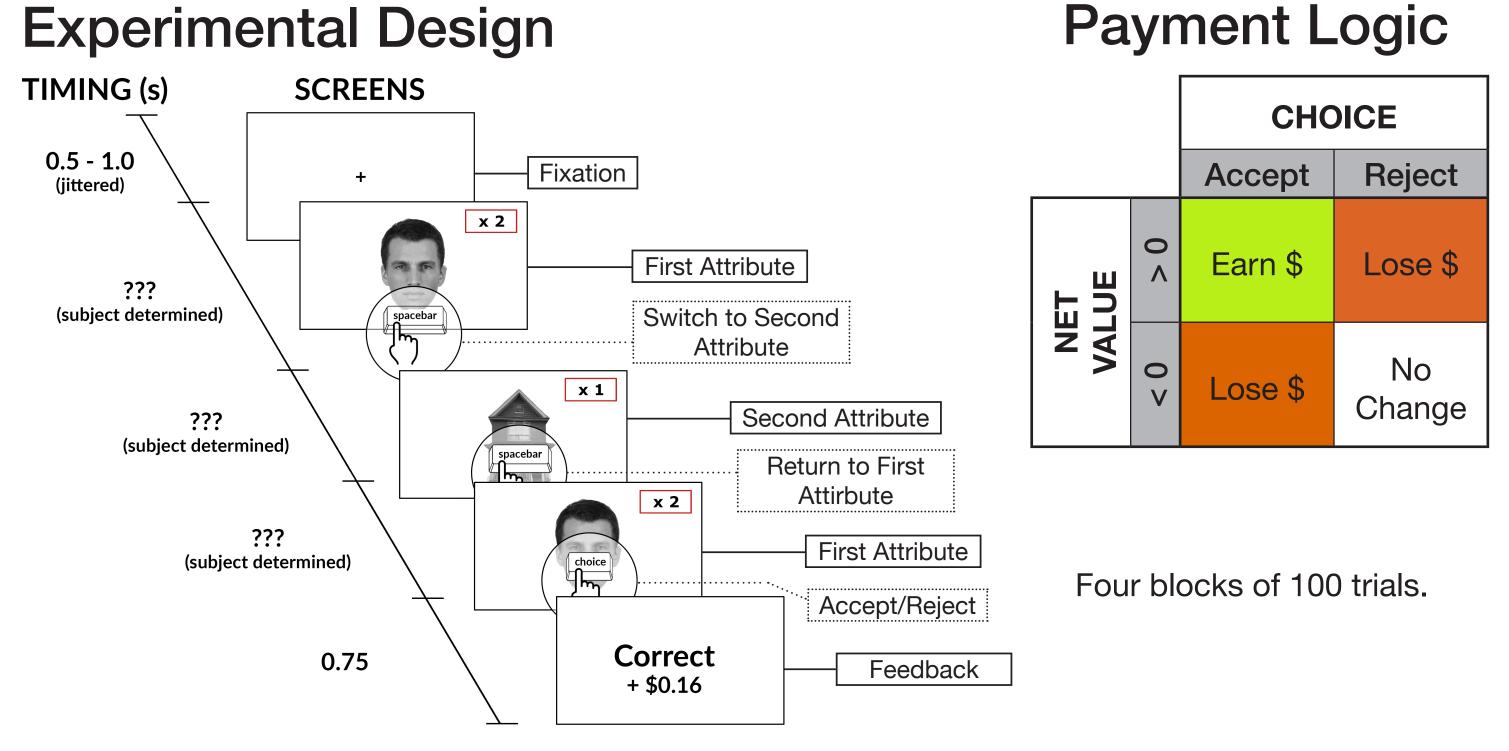


101 morphs, with values from -\$1.00 to \$1.00, were created. Morphs varied linearly in \$0.02 increments.

Net Value

Attribute Pair Example

Base Value

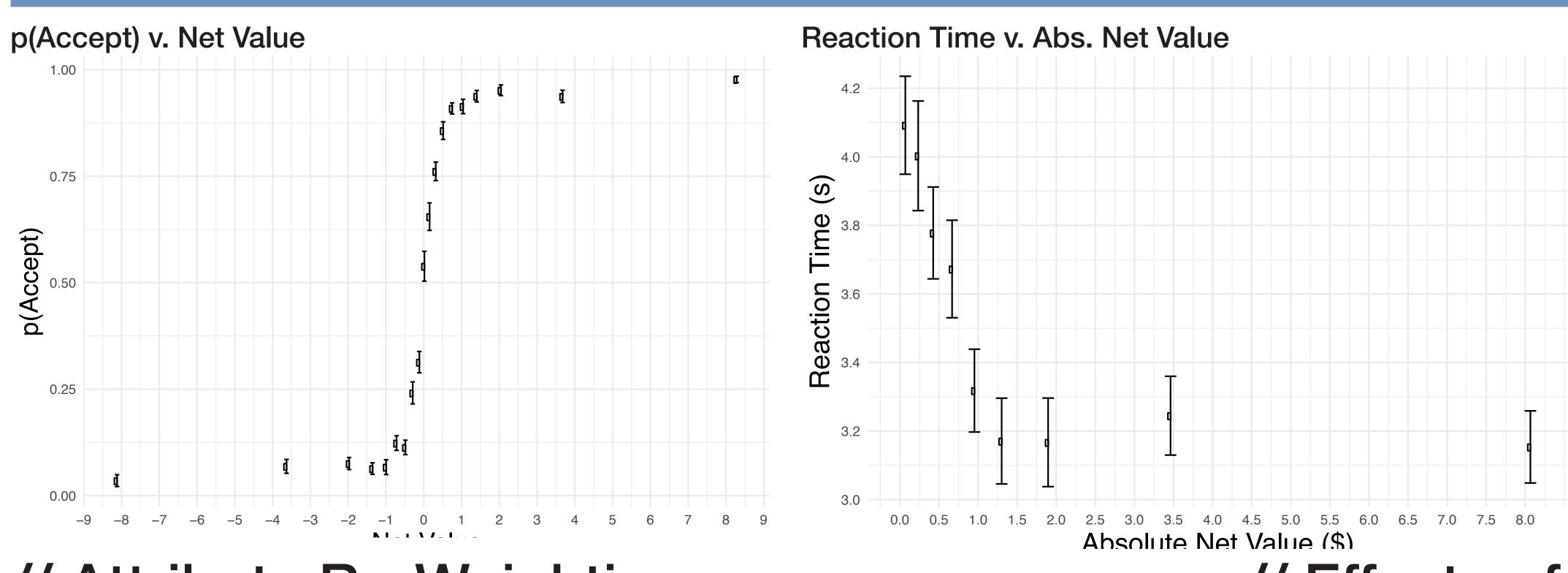


// ANALYSIS

- 1. Mixed effects regressions to predict choice and accuracy.
- 2. Hierarchical Bayesian drift diffusion modeling (HDDM ²) of the parameters:
- a (boundary): # of multipliers
- t (nondecision): # of fixations
- **V** (drift rate): $\beta_0 + \beta_1^* Face_{M1} + \beta_2^* House_{M1} + \beta_3^* Face_{M2} + \beta_4^* House_{M2} + \beta_5^* Face_{M3} + \beta_6^* House_{M3}$ where $\beta_1 - \beta_6$ are the attribute weightings (e.g. $Face_{M2}$ is a Face stimulus with a weight of 2)

// RESULTS

// Basic Psychometrics



Fixation Count v. Abs. Net Value

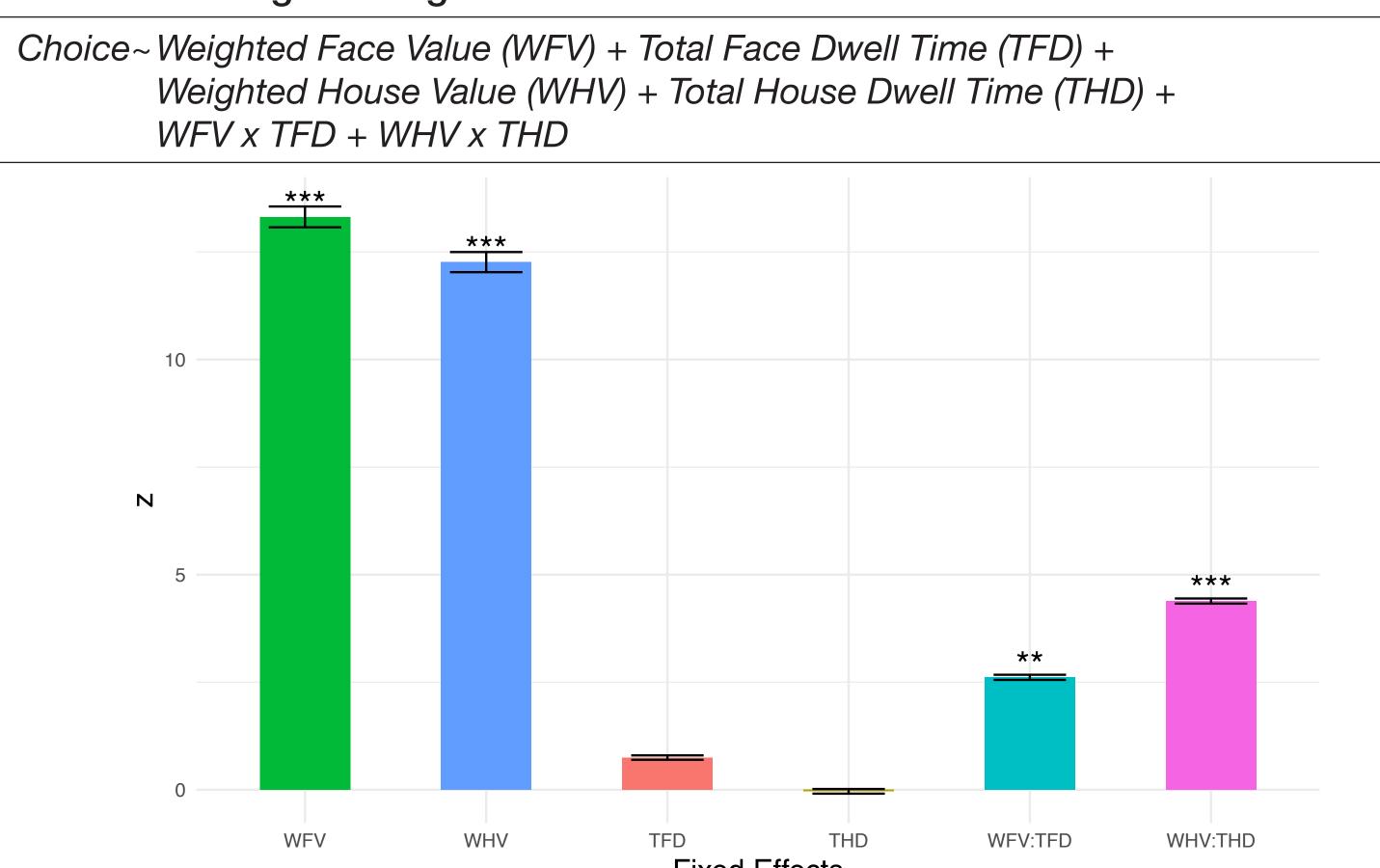
// Attribute Re-Weighting

Ideal vs. Measured Multiplier Re-Weighting

- 1. Subjects effectively re-weighted both attributes at all multiplier levels
- 2. Subjects weighted faces significantly more strongly than houses at all multiplier level.

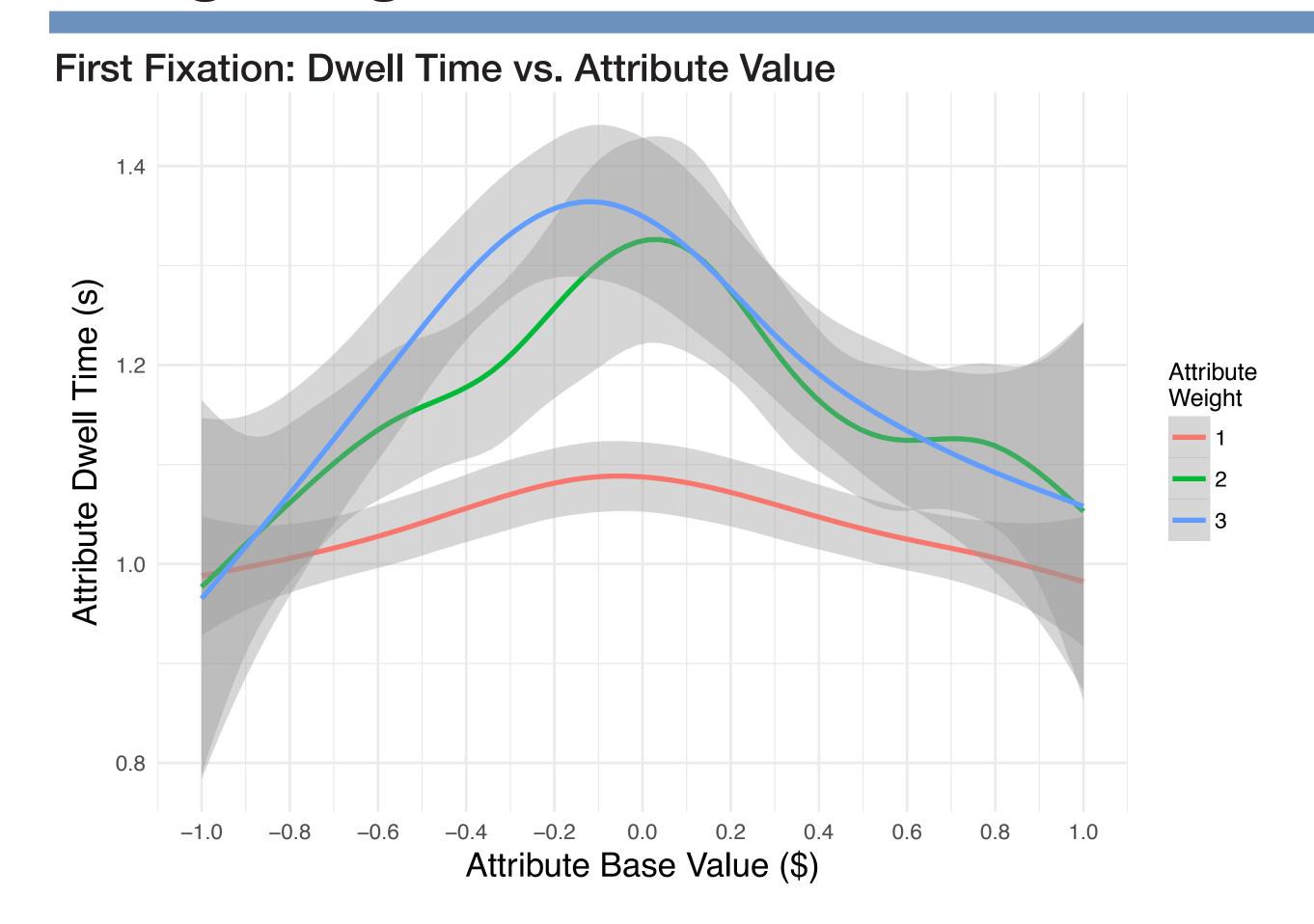
// Attention, Value and Choice

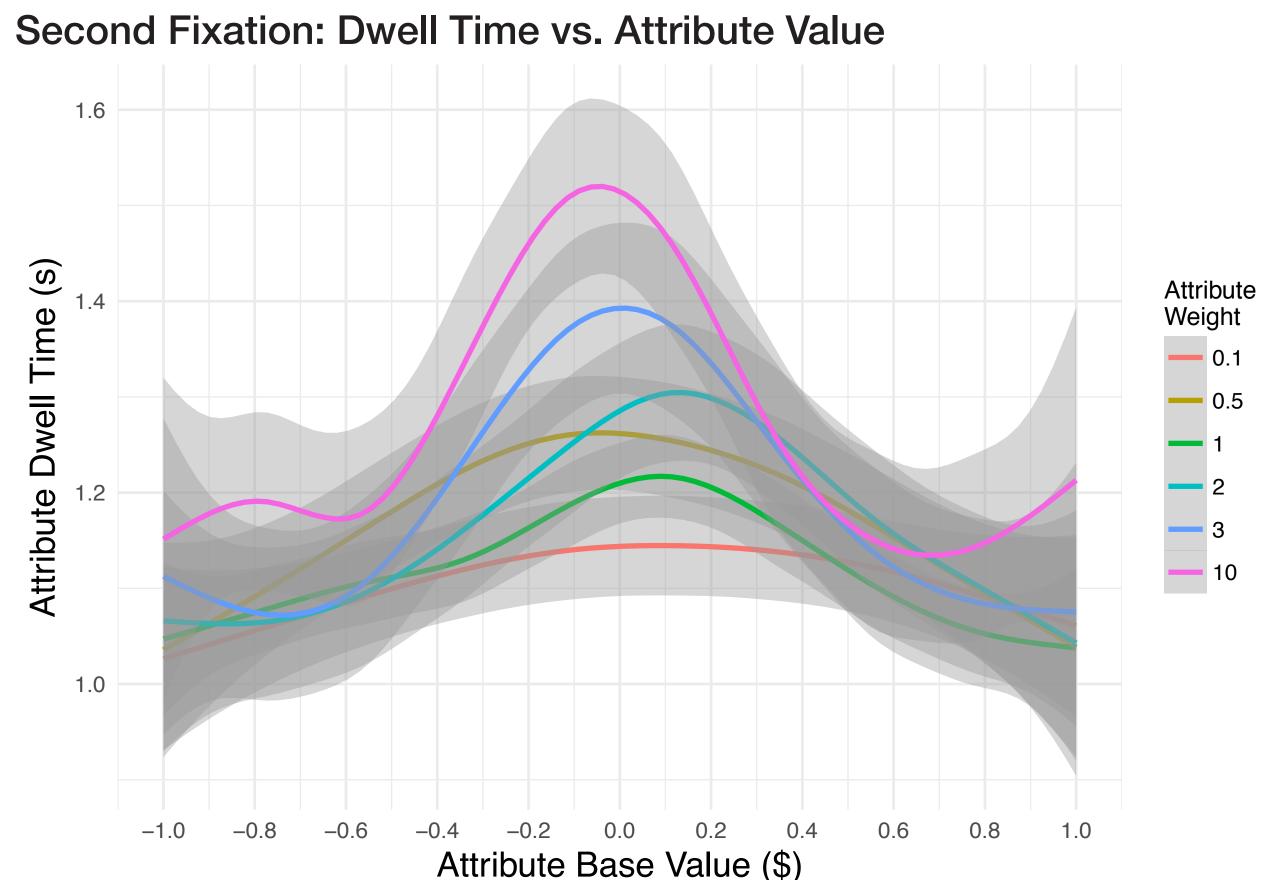
Mixed Effects Logistic Regression



- Attention alone is not predictive of choice.
- The interaction between attention (total attribute dwell time) and value is a significant predictor of subject decisions.
- Results suggest that attention amplifies the influence of the target attribute.

// Effects of Attribute Value & Weighting on Attention





Attribute attention is influenced by weighting, but only for the second fixation (when all decision information is known).

// ACKNOWLEDGEMENTS

Thanks to Steven Gu, Nardin Kirolos, Marcellus Singh for assistance in data collection, and Hause Lin, Michael Inzlicht and Wil Cunningham for valuable comments.

// FURTHER INFORMATION

Corresponding author: Daniel J Wilson

danielj.wilson@mail.utoronto.ca www.danieljwilson.com

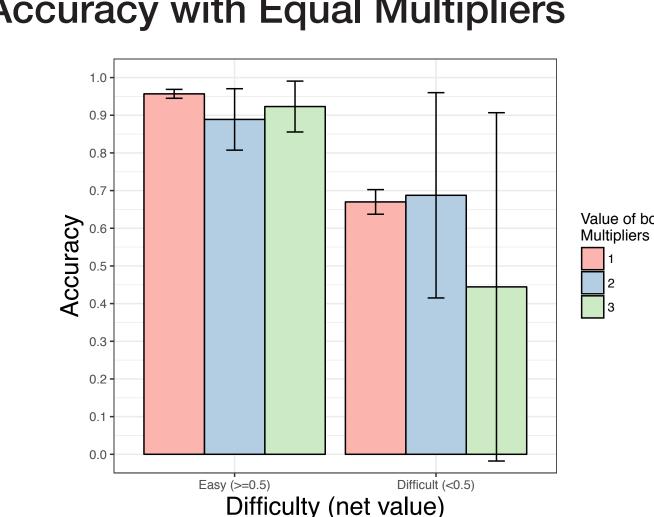
// Weighting, Value and Accuracy

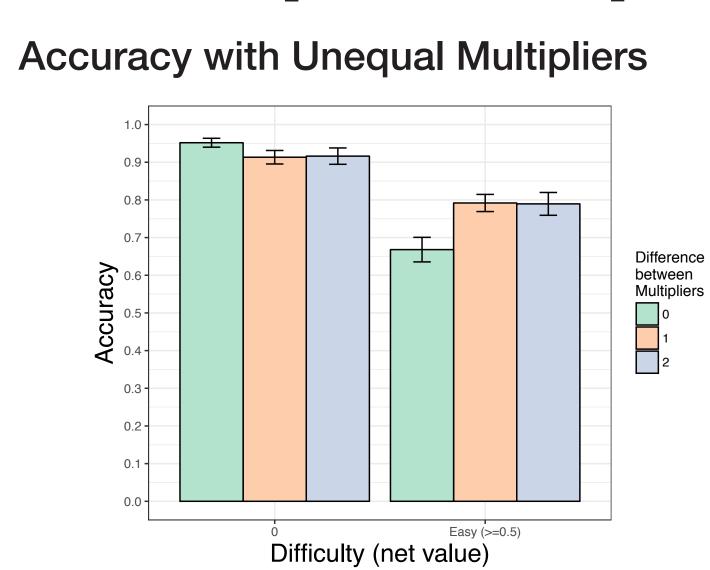
Attention Bias in Difficult Choices

If the number of re-weighted attributes = 0 it means that both attributes had weights of x1.

- For difficult trials (-\$0.50>Net Value>\$0.50), subjects were more accurate with attribute re-weighting than without.
- For easy trials this relationship reverses.
- This effect does not exist for trials with two equivalent multipliers.

Accuracy with Equal Multipliers





// DISCUSSION

- 1. The proposed paradigm can track attention while manipulating value and weighting of attributes.
- 2. Subjects are able to dynamically and flexibly re-weight attribute values.
- 3. More accessible or discernable attributes may tend to be overweighted.
- 4. Attention, as measured by attribute fixation duration, is not random. It is affected by value and weighting.
- 5. Going forward fMRI and EEG will be used to localize the neural correlates of attribute evaluation and weighting.

// REFERENCES

- 1. Belton, Valerie. (1986). A Comparison of the Analytic Hierarchy Process and a Simple Multi-Attribute Value Function. European Journal of Operational Research 26 (1): 7–21.
- 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