Attention and value integration in multi-attribute choice

Daniel J Wilson[1], Cendri Hutcherson[1]
[1]Department of Psychology, University of Toronto

// BACKGROUND

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

$$Summed\ Value = w_1{*}a_1 + w_2{*}a_2 ... w_n{*}a_n$$

Making good choices requires assigning weights to attributes in a flexible manner, informed by context [2].

Choice biases can result from difficulty in evaluating attributes or difficulty in assigning them proper weights [3,4].

// GOALS

1. Paradigm Confirmation. Can we explicity track attention to attributes and link to final choice people make?
2. Determine whether and how people are able to flexibly re-weight attributes.

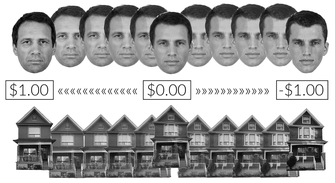
3. Examine interaction between attention and value/weight.

// METHODS

1. Subjects (n=23) learned to interpret 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.

Stimuli

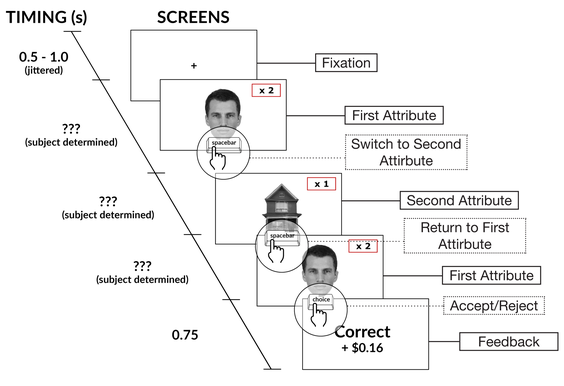


101 morphs, with values from -$1.00 to $1.00 were created. Morphs varied lineraly in $0.02 increments.

Attribute Pair Example

Base Value	
$0.50	-$0.34
Weighted Value	
$0.50	-$0.68
Net Value	

Experimental Design

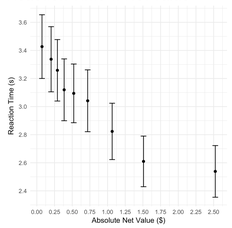


100 trials with no multipliers. 3 blocks of 100 trials with multipliers.

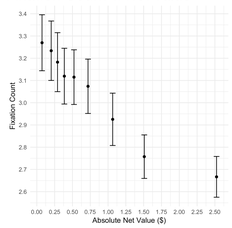
// RESULTS

// Basic Psychometrics

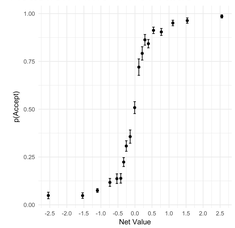
Reaction Time v. Net Value



Fixation Count v. Net Value

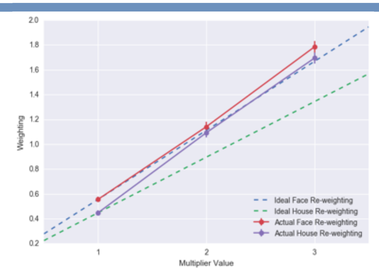


Reaction Time v. Net Value



Basic psychometric plots confirm expected behavior.

// Attribute Re-Weighting: Bias?



Ideal vs. actual re-weighting.
"Ideal" lines are drawn by multiplying the drift value estimate at attribute baseline by the re-weighting multiplier. Error bars are standard deviations clustered by subject.

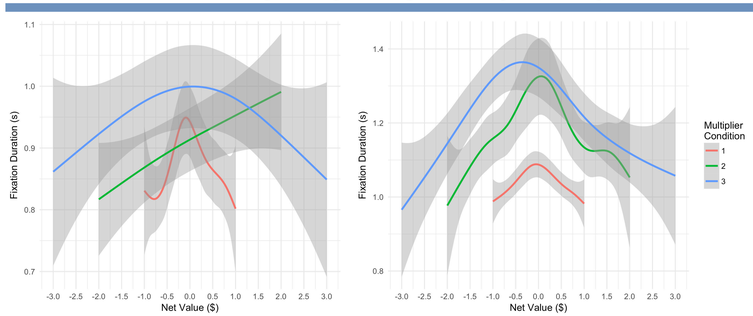
Modeling

Group drift values were calculated by fitting a hierarchical Bayesian drift diffusion model (HDDM)[5]. Parameters modeled:

a (boundary): # of multipliers
$\mathbf{T_{er}}$ (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 the β coefficients (β_1-β_6) are the subject weightings of the multipliers (e.g. $Face_{M2}$ is a Face stimulus with a multiplier of 2)

// Attribute Re-weighting: Cognitively Costly?



(A) Subject accuracy as a function of net value. Multiplier condition refers to the number of multipliers applied to attributes in the trial (0, 1 or 2). **(B)** First fixation duration as a function of the value (with multiplier) of the first viewed attribute. Multiplier condition refers to the value of the multiplier (1, 2 or 3). **(C)** Second fixation duration as a function of the value (with multiplier) of the second viewed attribute. Multiplier condition refers to the value of the multiplier (1, 2 or 3).

Two sources of bias were found in re-weighting trials:

1. Subjects weighted faces significantly more strongly than houses at all multiplier levels.

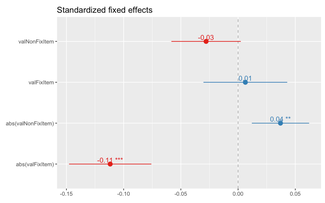
2. Taking a multiplier of 1 as baseline (i.e. those trials in which the value was the same as the learned value), subjects significantly over-estimated the re-weighting effects of multipliers applied to attributes.

// Attention, value and choice

Mixed effects logistic regression:

Choice ~ FaceValue + FaceAttention
+ HouseValue + HouseAttention
+ FaceValue:FaceAttention
+ HouseValue:HouseAttemtion

found choice was not predicted by attention alone (ps > 0.455), but the *interaction* between attribute values and attention was a significant predictor of choice (ps < 0.009).



Mixed effects linear regression:

log(2nd Attended Attrib. Dur.) ~ β0
+ β1 * Value Attended Attrib.
+ β2 * Value Unattended Attrib.
+ β3 * abs(Value Attended Attrib.)
+ β4 * abs(Value Unattended Attrib.)

found the duraction of the second fixation was affected not just by the absolute raw (un-multiplied) value of the attended attribute (b = -0.188, SE = 0.031, p = 1.16e-09), as could be expected, but was also significantly affected by the absolute raw value of the *unattended* attribute (b = 0.063, SE = 0.022, p = 0.004).

// DISCUSSION

Attribute value and weighting affect attention and choice.

Subjects systematically overweight attributes that have been re-weighted (increased in importance). Weighting is biased in favor of the face attribute over the house attribute. This may be due to the fact that the house morphs are more difficult to decipher than the face morphs.

Attention, as measured by attribute fixation duration, is not random. It is affected by value and weighting, and even by un-attended attributes.

Multipliers, difficulty and accuracy interact in non-intuitive ways.

// FUTURE DIRECTIONS

Modeling
Develop a value-based attentional drift diffusion model that can incorporate information on attribute weights and values.

Imaging
Collect functional magnetic resonance imaging and electroencephalogram data in order to localize the neural correlates of attribute evaluation and weighting.

Sticky Weights
Employ endogenous valuation to examine whether there are certain situations in wihch re-weighting is systematically compromised.

// REFERENCES

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// Further Information

Corresponding author: Daniel J Wilson
danielj.wilson@mail.utoronto.ca
www.danieljwilson.com