Attention and value integration in multi-attribute choice

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// BACKGROUND

Multi-attribute, value-based decisions, describe the majority of our life choices [1].

The final value = combo of weighted attribute evaluations = evaluation of attribute (how 'good' it is), weighting of attribute (how 'important' it is) [2].

Attention can bias choice [3,4].

Poor weighting can result in incorrect decisions, even if attributes are correctly evaluated.

// GOALS

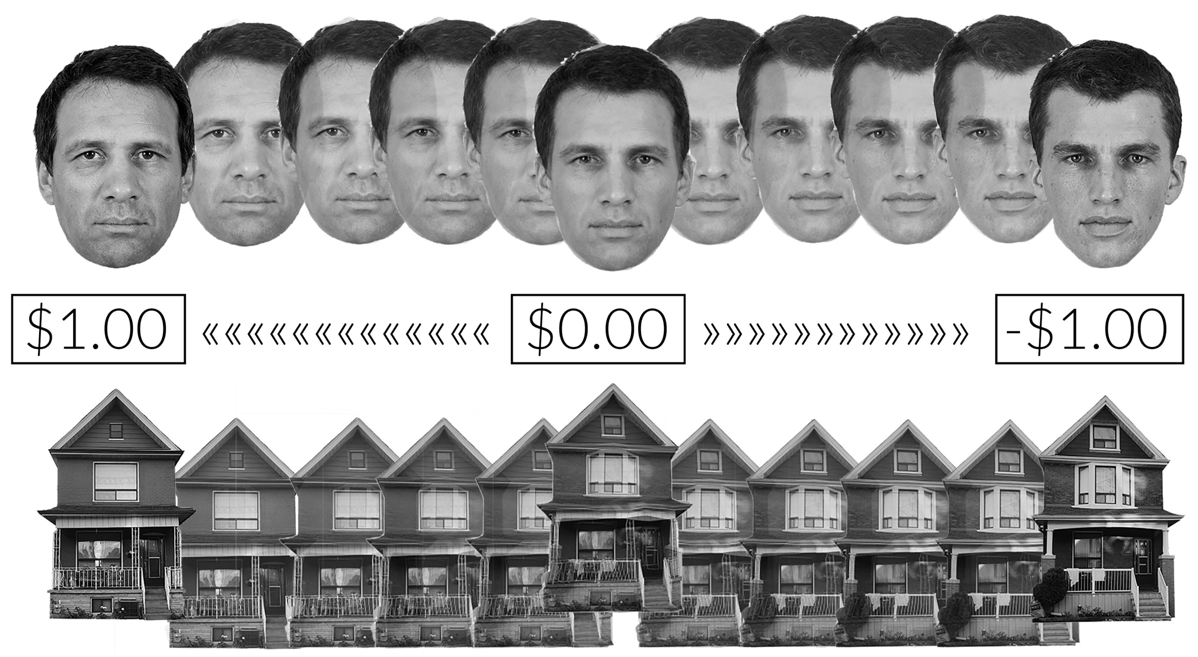
1. Examine re-weighting. Are people able to re-weight based on changes in context? Is it "costly"? How does re-weighting affect accuracy/RT? Does it lead to systematic biases?

2. Examine interaction between attention and value/weight. Should drift diffusion models account for attribute value?

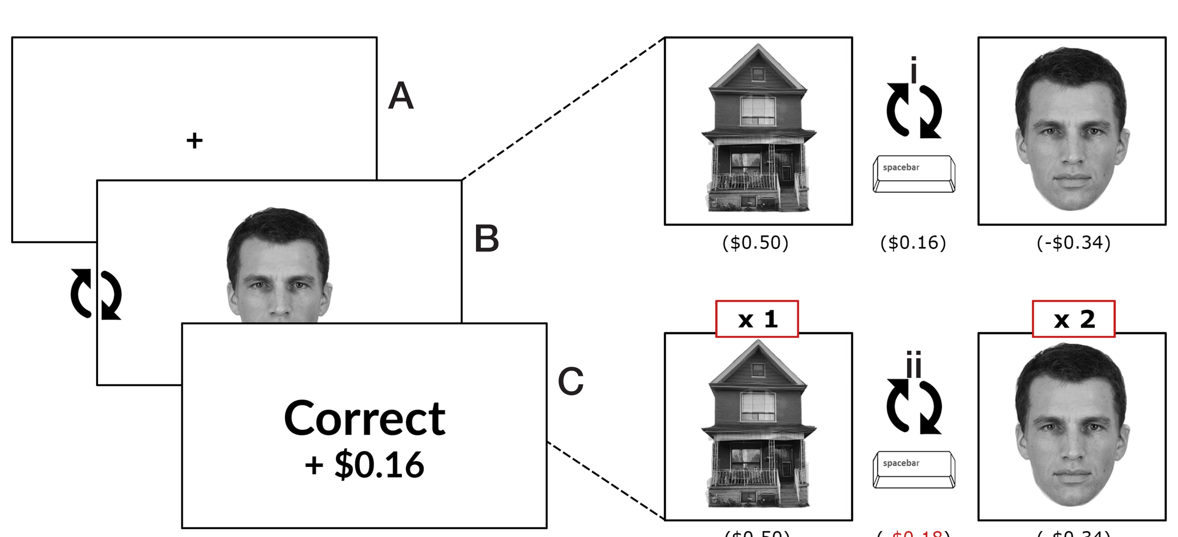
// METHODS

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.



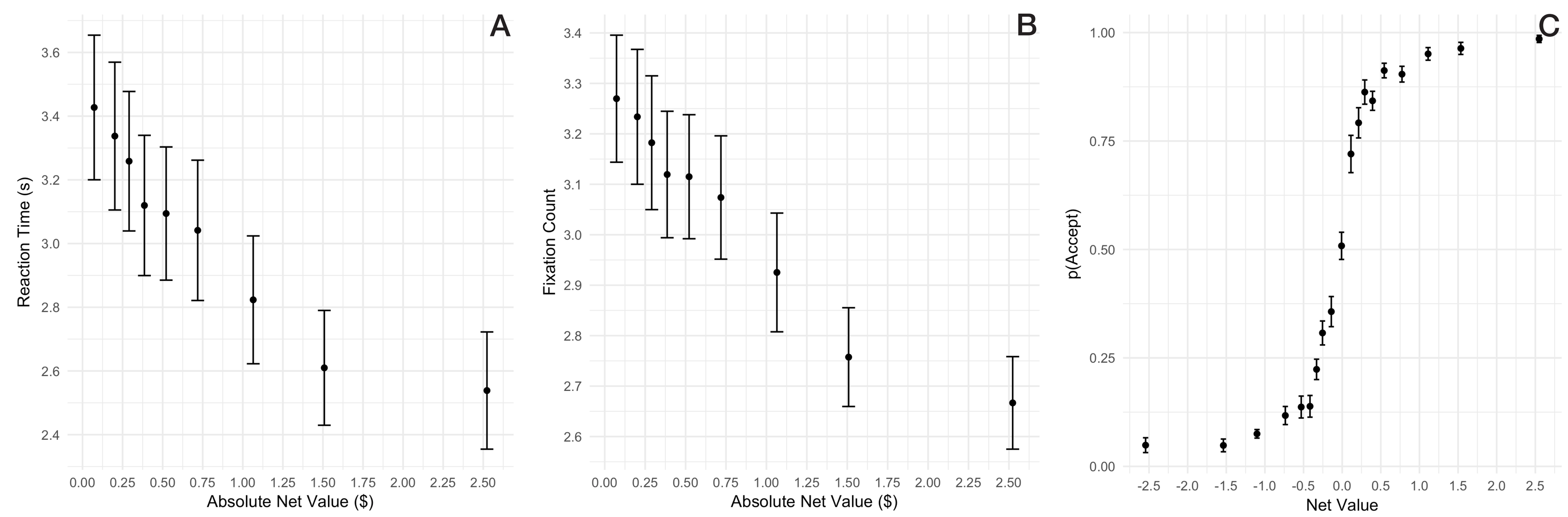
Stimuli.
101 morphs, with values from -$1.00 to $1.00 were created.
Morphs varied lineraly in $0.02 increments.



Experiment Design.
Trial logic: **(A) Fixation cross.** Jittered 0.5 - 1.0 s. **(B) Attribute presentation.** Randomly selected pair of image morphs (1 face and 1 house). Viewed individually, but swapped between by the press of the spacebar. Free response time. **(C) Feedback.**
Trial examples: **(i)** trial without re-weighting multiplier. **(ii)** Re-weighting trial. In this example the face attribute has doubled in absolute value, changing the sign of the summed value of the attributes, and therefore changing the correct decision (accept/reject).

// RESULTS

// Basic Psychometrics



Basic psychometric plots confirm expected behavior.

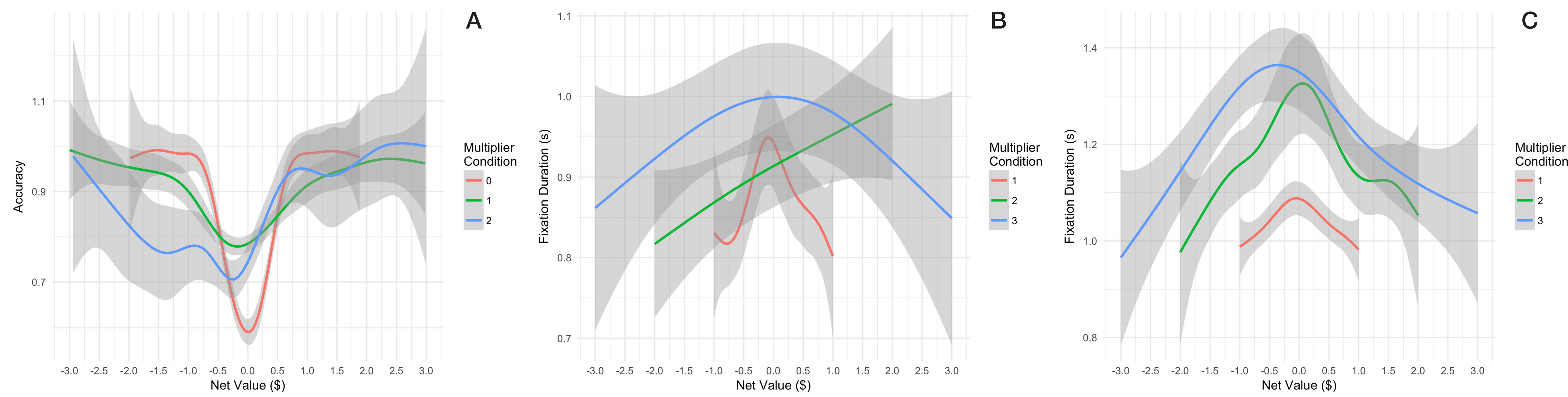
(A) Reaction time decreases with an increase in absolute value of the attribute combination (attribute 1 + attribute 2), which corresponds to an "easier" decision.

(B) The fixation count (the number of times a subject switches between images) also decreases as absolute value increases.

(C) Probability of accepting the attribute combination as a function of the net value of the attributes.

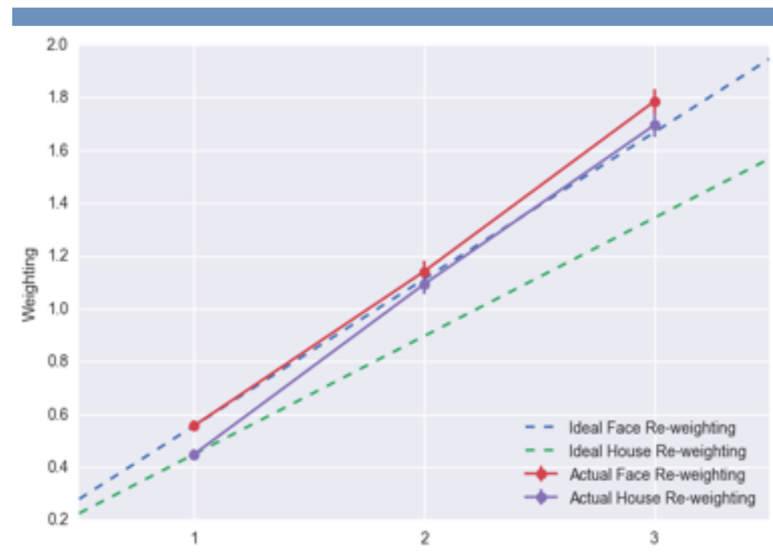
Black circles indicate binned subject means, containing approximately equal numbers of trials. Bars are standard error bars clustered by subject.

// 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).

// 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): $\beta_0 + \beta_1 * Face_{M1} + \beta_2 * House_{M1} + \beta_3 * Face_{M2} + \beta_4 * House_{M2} + \beta_5 * Face_{M3} + \beta_6 * House_{M3}$

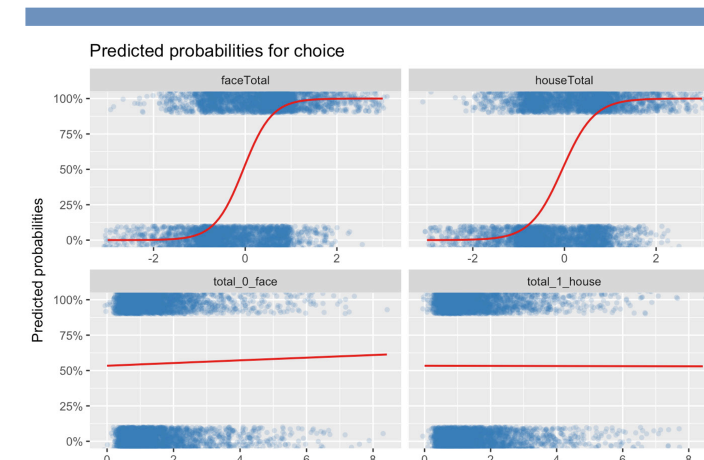
where the β coefficients (β_1-β_6) are the subject weightings of the multipliers (e.g. $Face_{M2}$ is a Face stimulus with a multiplier of 2)

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.

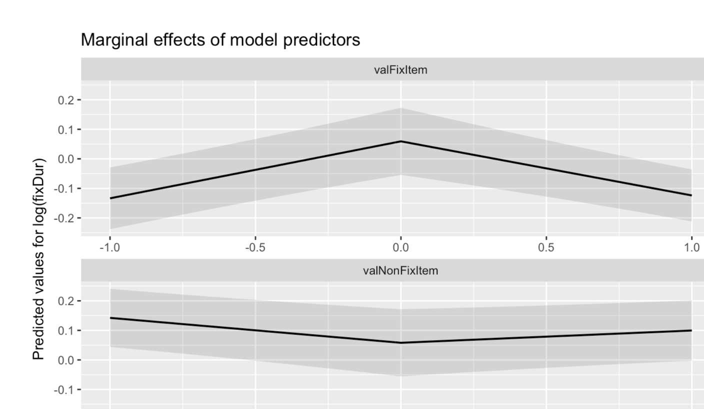
// Attention, value and choice



Mixed effects logistic regression:

Choice ~ FaceValue + FaceAttention
+ HouseValue + HouseAttention
+ FaceValue:FaceMultiplier
+ HouseValue:HouseMultiplier

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 duration 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

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