The Role of Reward Magnitude in Multi-Attribute Categorization Decisions

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Abstract

Reward has been shown to affect memory and attention, but whether it influences category decisions is still unclear. In two studies, participants first underwent a category learning phase. Correct categorizations yielded different rewards for the exemplars (high vs. low). A test phase followed, including novel items. Categorization accuracy decreased for low reward stimuli. A Bayesian model analysis on the test phase decisions relates this effect to over-generalization of high reward stimuli.

Theory

Research Question 1

- Monetary reward is one of the main drives in human decision making
- Reward is positively related to stimulus attention and declarative memory (Miendlarzewska, Bavelier, & Schwartz, 2016)
- Does reward magnitude affect learning in category decision making?

Research Question 2:

- Established models of human categorization are still unrelated to reward magnitude:
- Can models of exemplar memory account for potential effects of reward on *exemplar memory strength* or *exemplar generalization* (General Context Model, Nosofsky 2011)?

Hypotheses

H1 Exemplar Memory Strength:

Memory strength is higher for high reward exemplars than for low reward exemplars/controls (GCM: $V_{high} > V_{control}$)

H2 Exemplar Generalization:

High reward exemplars generalize stronger than low reward exemplars/controls (GCM: $c_{high} < c_{control}$)

General Context Model (Nosofsky 2011)

Stimulus Similarity in the GCM

- ("Manhatten") distance d_{ij} is calculated between values x_{jm} of **exemplar** j (in memory) and the values y_{im} of the current **stimulus** i on attribute dimensions m
- Differences are weighted by attribute attention w_m
- Summed distance is transformed to similarity s_{ij}

$$d_{ij} = \sum_m w_m \cdot |y_{im} - x_{jm}|;$$

$$s_{ij} = e^{-c_j \cdot d_{ij}}$$

- Decreasing *generalization gradients* c_j boost influence of more distant exemplars *j* on similarity
- Final choice probability $p(A|i)$ = similarity of exemplars from category A relative to exemplars from all *K* categories

$$p(A|i) = \frac{\sum V_j s_{ij(A)}}{\sum V_j s_{ij(K)}}$$

- Exemplar *memory strength* V_j changes probabilities

(H1) If V_j increases with reward magnitude, then

⇒ Higher accuracy for high reward exemplars

⇒ General choice bias towards categories of most similar high reward exemplars

(H2) If c_j decreases with increasing reward, then

⇒ Stronger generalization for high reward exemplars

⇒ No increase in accuracy for high reward exemplars

⇒ Less accurate decisions for low reward exemplars

Method Overview

Procedure

Task: categorize stimuli (2 categories), respect attributes

Phase 1 – Categorization Training

- 120 and 100 decision trials: 10 stimuli repeated in 12 and 10 blocks, in Study 1 and 2, respectively
- Correct decisions immediately rewarded (bonus payment)

Phase 2. Categorization Test

- Trained and new stimuli, no feedback (250 trials in Study 1, 132 trials in Study 2)

Training Manipulation (within):

- *Specific exemplars* from both categories yield ten times higher *reward* than other exemplars *(high vs. low)*

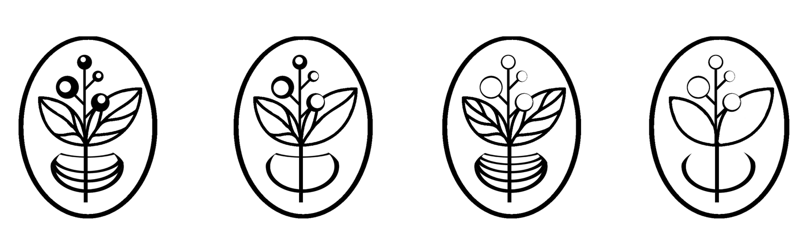
Experimental Conditions (between)

- *Study 1.* ***Baseline*** *vs.* ***2 Unequal Rewards conditions***
- *Study 2.* ***Baseline*** *vs.* ***1 Unequal Rewards condition***
- ***Baselines:*** all exemplars yield ***equal reward*** (cet. par.)

Stimuli

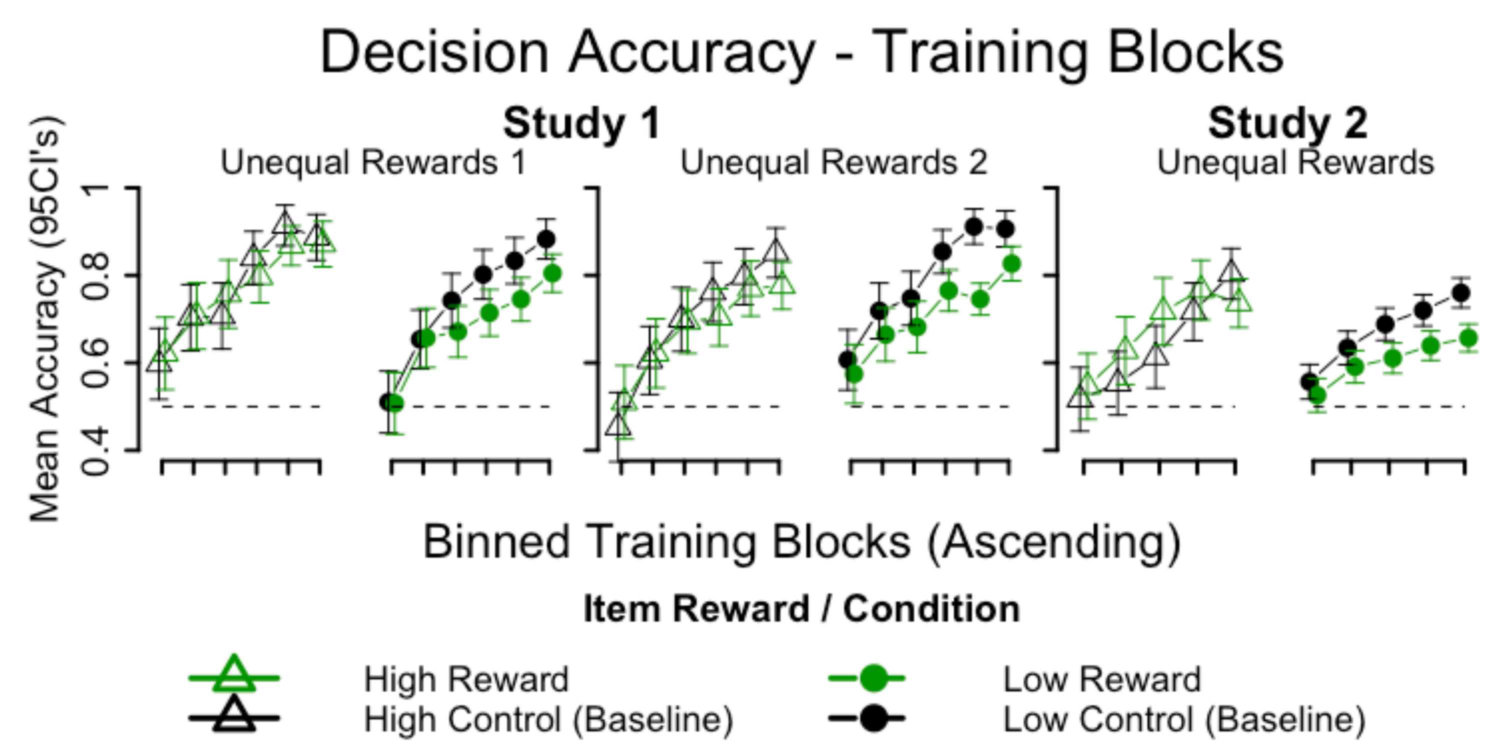
- Fictitious plants, combinations of m=3 quantitative attributes (berries, leafs, base), each with 4 (Study 1) or 5 (Study 2) possible values
- Category structure: 2 categories (A and B) with: Criterion = -mean($x_{m(1\text{-}3)}$) + .34$x_{m=1}$+.34$x_{m=2}$+..32$x_{m=3}$ with category = A if Criterion > 0
- Stimulus set and reward manipulation selected after stimulus sampling and model simulations

Stimulus Examples



Participants

- *Study 1 (Lab).* Adults, n=111 (72 female, *M(age)*=24.9, *SD*=6.4) randomly assigned to three conditions; payment: bonus + lump sum, or + course credit.
- *Study 2 (Online, Mturk, preregistered on OSF).* Adults, n=204 (93 female, *M(age)*=34.9, *SD*=10.5) randomly assigned to two conditions; payment: lump sum + bonus.



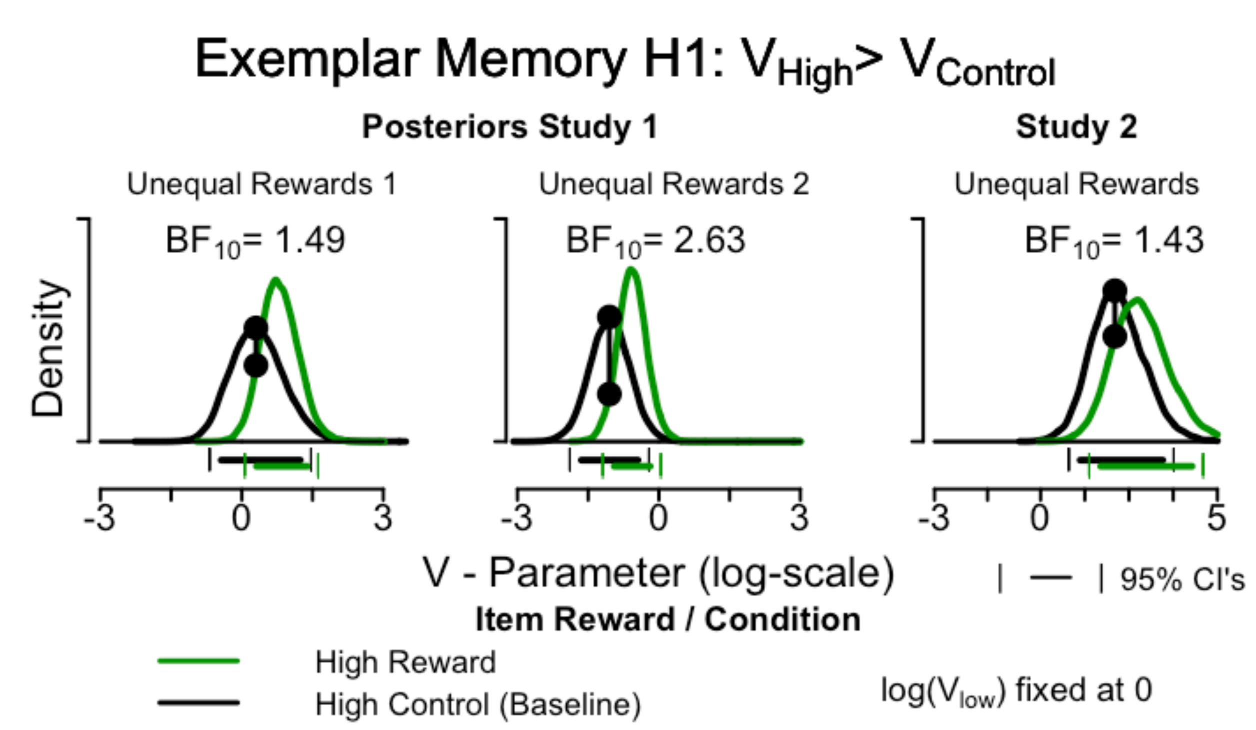
Decision Training Performance– Results

- Reward differences reduced accuracy for low reward exemplars in both studies (sign. effects in mixed model analyses)
- Equal performance for high reward exemplars between conditions
- Most reliable effect in ***Study 2:***
- Bayesian GCM analysis relates this effect to generalization, not memory strength

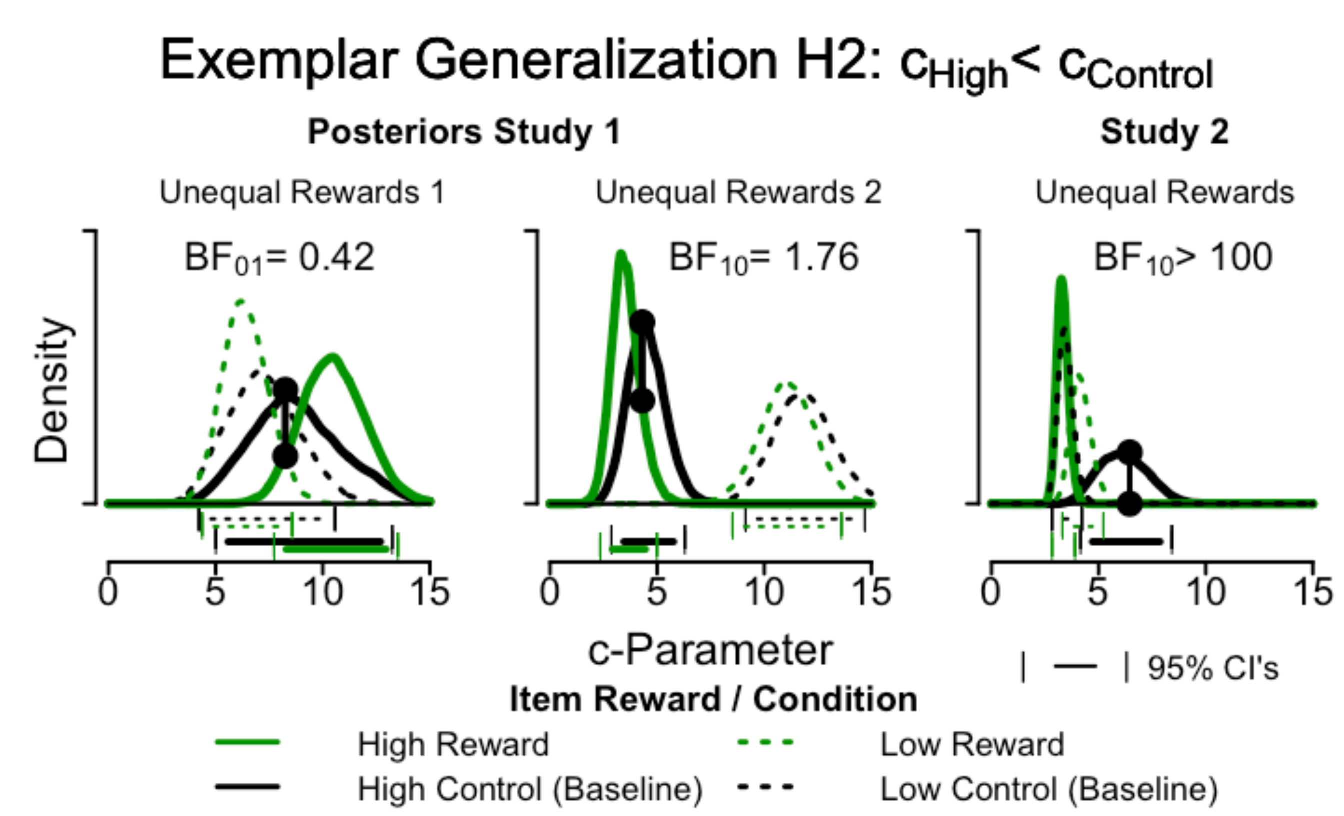
Test Phase – Hierarchical Bayesian Modeling

Model classification on test phase decisions

- ***Study 1.*** GCM ~ 80% of p's, ~ 20% other & guessing
- ***Study 2.*** GCM ~ 55% of p's, ~ 45% other & guessing



- No support for a reliable influence of reward on memory strength or choice biases in both studies



- ***Study 1.*** No evidence for H2; Possible issues: sample size, stimulus characteristics (large c's) ⇒ stimuli refined and higher power in Study 2
- ***Study 2.*** Strong evidence for H2: high reward exemplars were generalized stronger

Conclusion

- Overall, reward differences in category learning counteract the maximization of decision performance in both studies
- No increase in accuracy for high reward exemplars
- Instead, reward differences reliably impeded decision performance for low reward exemplars
- This effect on categorization seems related to over-generalization of high reward exemplars
- More research is needed

References

Juslin, P., Jones, S., Olsson, H., & Winman, A. (2003). Cue abstraction and exemplar memory in categorization. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(5), 924.

Miendlarzewska, E. A., Bavelier, D., & Schwartz, S. (2016). Influence of reward motivation on human declarative memory. *Neuroscience & Biobehavioral Reviews*, *61*, 156-176.

Nosofsky, R. M. (2011). The generalized context model: An exemplar model of classification. *Formal approaches in categorization*, 18-39.