Multiattribute Decision-making in Macaques Relies on Direct Attribute Comparisons

Aster Q. Perkins, Zachary S. Gillis, Erin L. Rich

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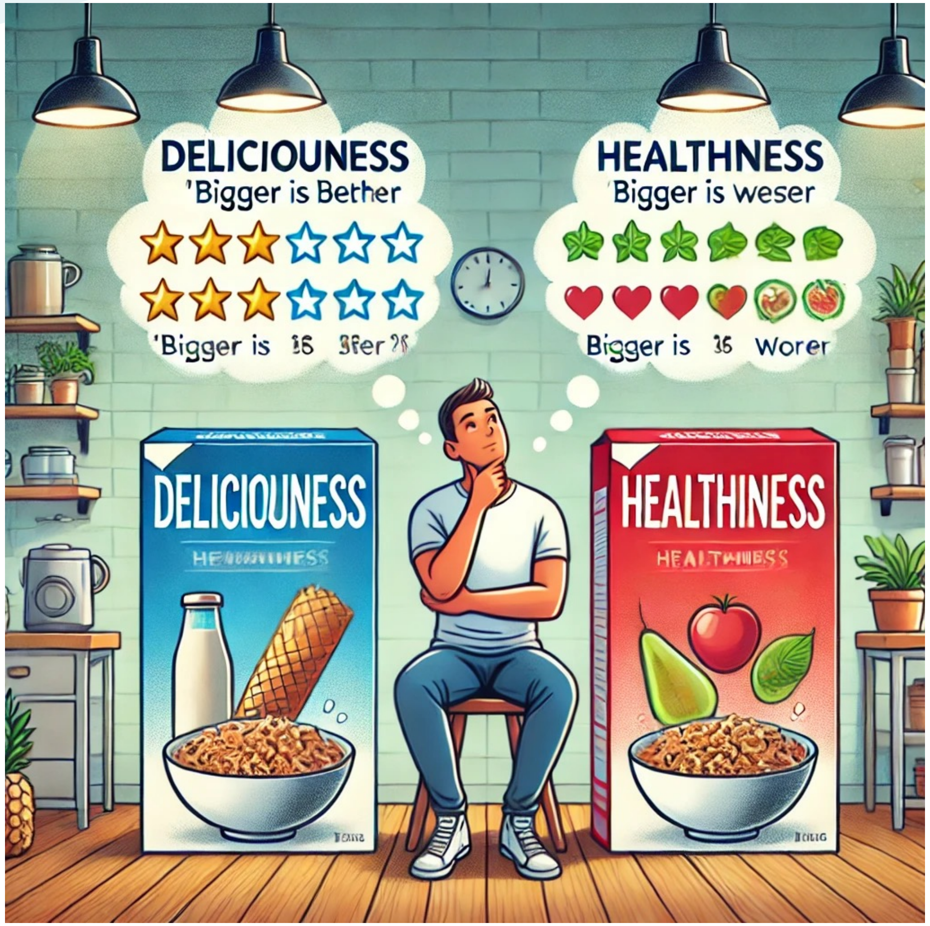
Changfa FU

We acknowledge and pay respect to the Traditional Owners of the lands upon which our campuses are situated

What makes your food decisions?



Source: DALL-E

Existing Literature

Real-world decisions involve multiple attributes (e.g., cost, quality, quantity).

- Question: How info is used

Traditional Decision-Making Models:

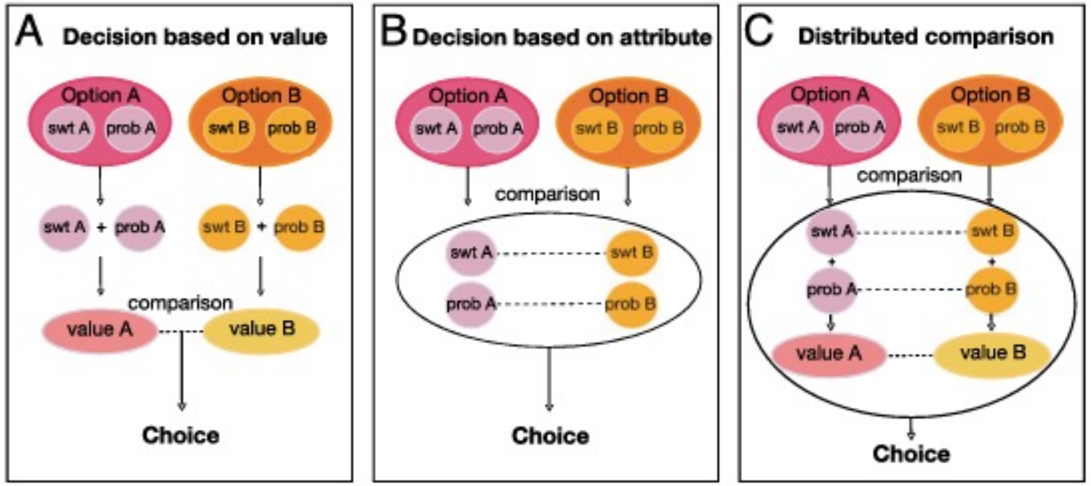
- Compute integrated value (utility) for options (Padoa-Schioppa, 2011).
- Compare integrated option values (Rustichini & Padoa-Schioppa, 2015).
- Neural response for value integration (Hunt et al., 2015).

Behavioural anomalies like context effects suggest other computations (Landry & Webb, 2021)

- Decision Field Theory (Roe, Busemeyer, & Townsend, 2001).
- Attentional Drift Diffusion Models (Fisher, 2021).
- Distributed Theory of Decision-Making (Hunt & Hayden, 2017).

Direct Attribute Comparisons (Perkins et al., 2024)

- Attribute-specific processing (Perkins & Rich, 2021).
- Goal-directed decision making (Rangel & Hare, 2010).



Study Aim

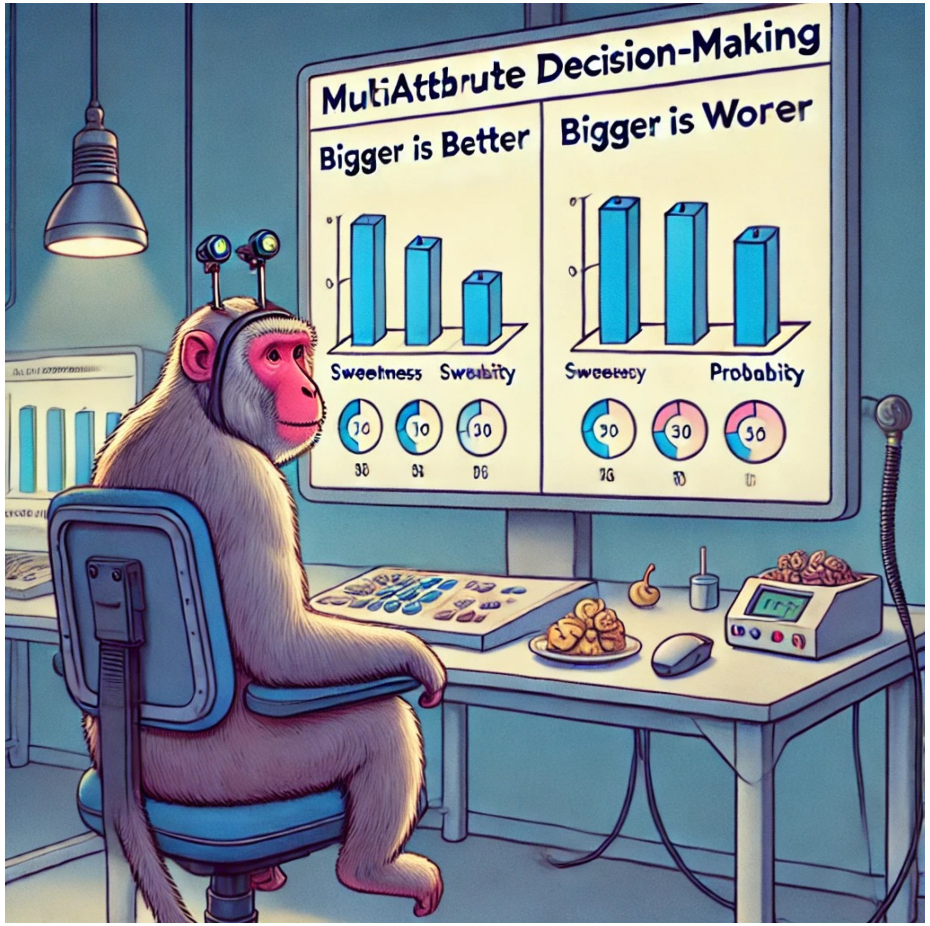
Research Gap

- Lack of clarity on whether decision-making processes involve direct comparisons of individual attributes or solely rely on integrated utility values.

Research Aim

- Test whether rhesus macaques show evidence of attribute-specific processing in a value-based decision-making task.
- Explore insights into the underlying cognitive processes and challenge traditional models that emphasize integrated utility computations.

Experiment Design: Subjects



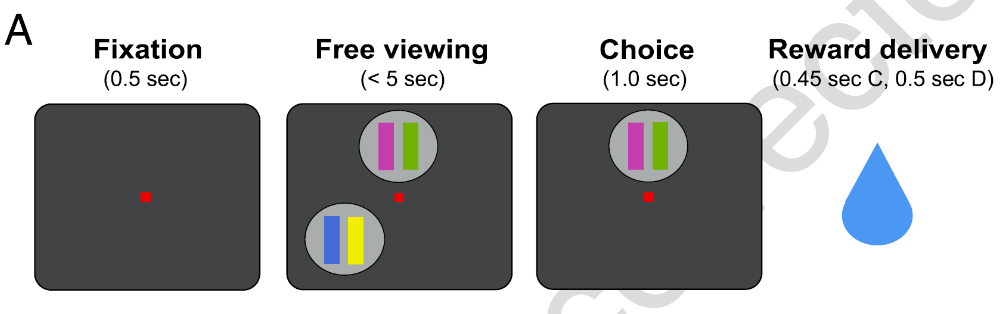
Subjects: Two adult male rhesus macaques (C & D)

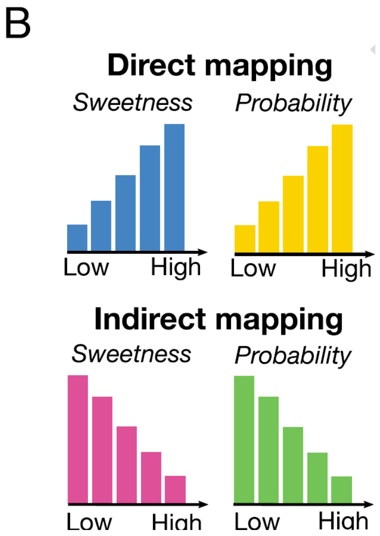
- 5 years old
- 11.8kg and 9.4kg
- Titanium head positioner surgically implanted

Setting:

- Sat in a primate chair
- In a darkened testing chamber
- Head-fixed facing an 18-in. computer monitor positioned 17 in. away
- Eye position monitored by an infrared eye tracker at a sampling rate of 400 Hz.

Experiment Design: Tasks





- Left bar: sweetness level (25-, 50-, 75-, 100-, or 125-mM sucrose solution)
- Right bar: probability level (10%, 30%, 50%, 70%, or 90%).
- Colors of the bars indicated whether the size of the bar positively or negatively correlated.
- Bar size and mapping randomly/ independently on each trial.

1. Gazed at the fixation point
2. Held a touch-sensitive bar for 550 msec
3. Two (80% of trials) or three (20% of trials) choice options on the screen randomly in a hexagonal arrangement around central fixation
4. <5sec to freely view the image
5. Make choice by holding gaze on any part of the desired option and releasing the touch-sensitive bar.
6. If correct, rewards or if improper, timeout

NB: Relative weighting of sweetness and probability, to balance subjective preference between the two attributes.

Statistical Analysis

- Accuracies and RTs
- Choice Regressions

$$X = \beta_0 + \beta_{\text{Prob}}\left(log\frac{ProbA}{ProbB}\right) + \beta_{\text{Swt}}\left(log\frac{SwtA}{SwtB}\right) \\ + \beta_{\text{SwtDirA}}SwtDirA + \beta_{\text{SwtDirB}}SwtDirB \\ + \beta_{\text{ProbDirA}}ProbDirA + \beta_{\text{ProbDirB}}ProbDirB \\ + \beta_{\text{PositionA}}PositionA + \beta_{\text{PositionB}}PositionB$$

- RT Regression

$$log(ReactionTime) = \beta_0 + \beta_{\text{SwtDiff}}SwtDiff \\ + \beta_{\text{ProbDiff}}ProbDiff + \beta_{\text{NumSwtInd}}NumSwtInd \\ + \beta_{\text{NumProbInd}}NumProbIn$$

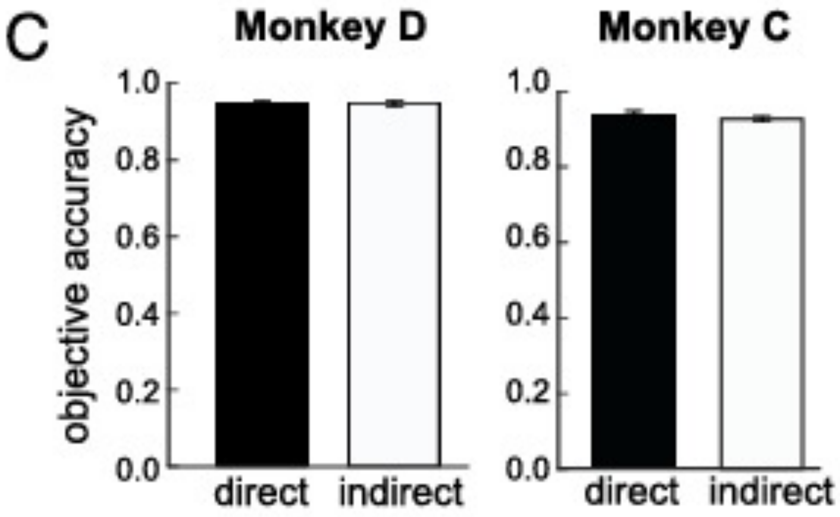
- Gaze Data Analysis
  - Regressions on Number of Fixations

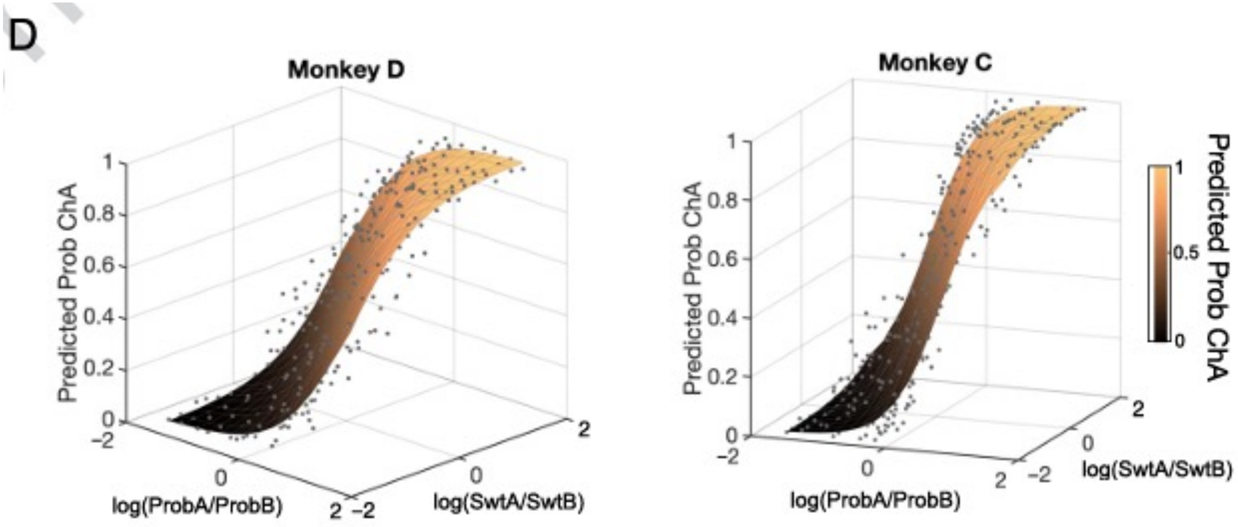
$$NumberFixations = \beta_0 + \beta_{\text{SwtDiff}}SwtDiff \\ + \beta_{\text{ProbDiff}}ProbDiff + \beta_{\text{NumSwtInd}}NumSwtInd \\ + \beta_{\text{NumProdInd}}NumProdInd$$

  - Regression on Fixation Duration

$$log(Fixation\ Duration) = \beta_0 + \beta_{\text{Swt|Prob}}Swt|Prob \\ + \beta_{\text{Ch|Unch}}Ch|Unch + \beta_{\text{Dir|Ind}}Dir|Ind \\ + \beta_{\text{FixVal}}FixValf + \beta_{\text{OtherAttSameOpt}}OtherAttSameOpt \\ + \beta_{\text{SameAttOtherOpt}}SameAttOtherOpt \\ + \beta_{\text{OtherAttOtherOpt}}OtherAttOtherOpt \\ + \beta_{\text{Swt|Prob*FixVal}}Swt|Prob * FixVal \\ + \beta_{\text{Ch|Unch*FixVal}}Ch|Unch * FixVal \\ + \beta_{\text{Dir|Ind*FixVal}}Dir|Ind * FixVal \tag{6}$$

Results: Monkeys Use Multiple Attributes to Make Optimal Choices

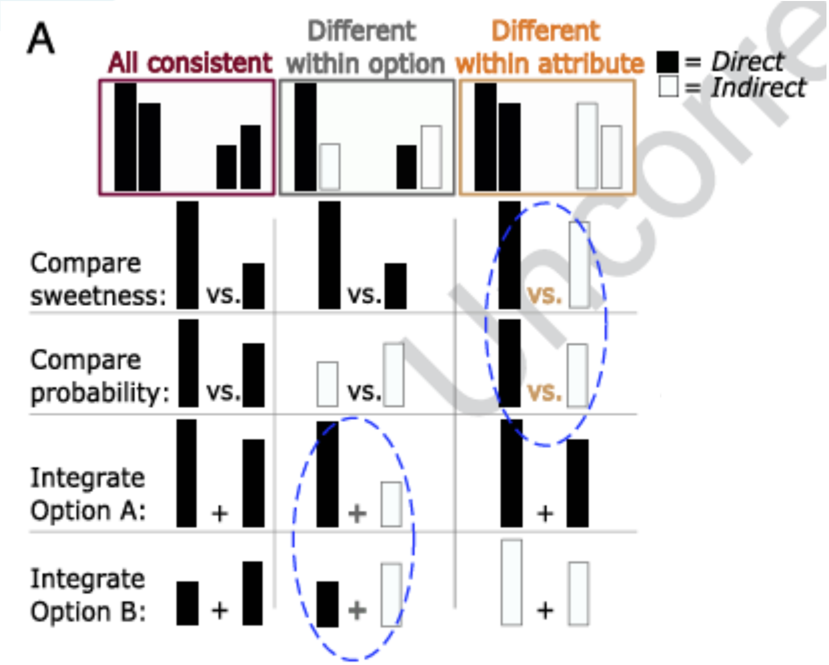




High objective accuracies, likely reflecting easier decisions

Magnitudes of attributes strongly predicted choices
Monkeys primarily used sweetness and probability info to guide decisions.
Monkeys tended to pick the option with higher sweetness and probability.

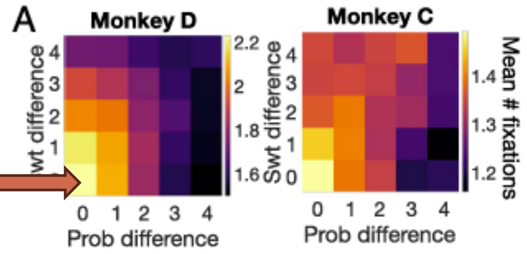
Results: Mapping Mismatches Impair Attribute Comparisons



Consistently less accuracy when mismatched

Results: Gaze Patterns during Multiattribute Choices

Looked more at option when choices becomes more difficult



Gaze transitions are consistent with attribute comparison

within attribute transitions

within option transitions

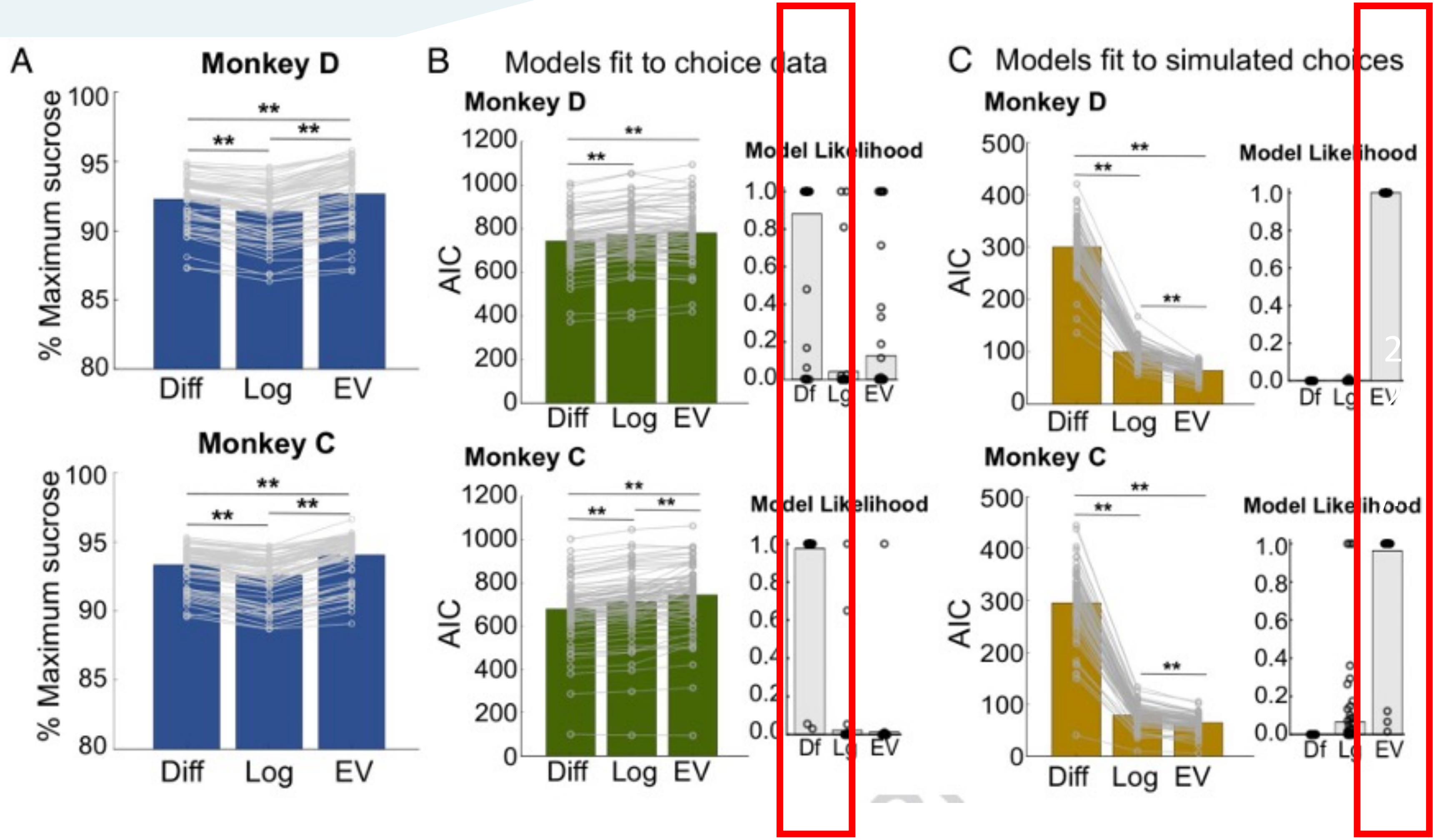
Proportional increase in both transitions

Results: Monkeys use separate attributes to make value-based choices, yet suboptimal.

EV:
Amount of Sucrose ×Prob of Receiving

Log:
Log ratio of each attribute

$Diff$:
Difference among attributes



Discussion: Attribute-level processes as a mechanism in multiattribute decision-making

Spontaneously direct comparisons of like attributes to arrive at a decision.

- No exclusion of the role for integrated value comparisons:
  - Either without or in parallel to.
- Natural tendency to use unintegrated attributes:
  - Context effect – within-attribute comparisons.
  - Attraction effect – accumulate attentional weights.
- Parallel comparisons of multiple variables:
  - Like attributes, integrated values, and attribute saliencies.
  - Distributed brain systems – **hierarchical arrangement** of many variables
- Consistent mappings within like attributes facilitate comparison in decision-making but not grouping.

Limitations & Implications

Small sample size

- Need research on biological variables such as age or sex

Task Complexity

- May introduce learning effects or other confounding variables

Interpretation of Gaze Patterns

- Gaze bias ?= preference ~⫫ choice
- May need additional neurophysiological measures

"Challenging" Traditional Models

- Direct comparison instead of integrated utility values

Cognitive Mechanism

- Possible role of attribute-specific processing

Future Research

- Extend to other animals and human research
- Revisit interpretation of neural correlate to choice behaviours

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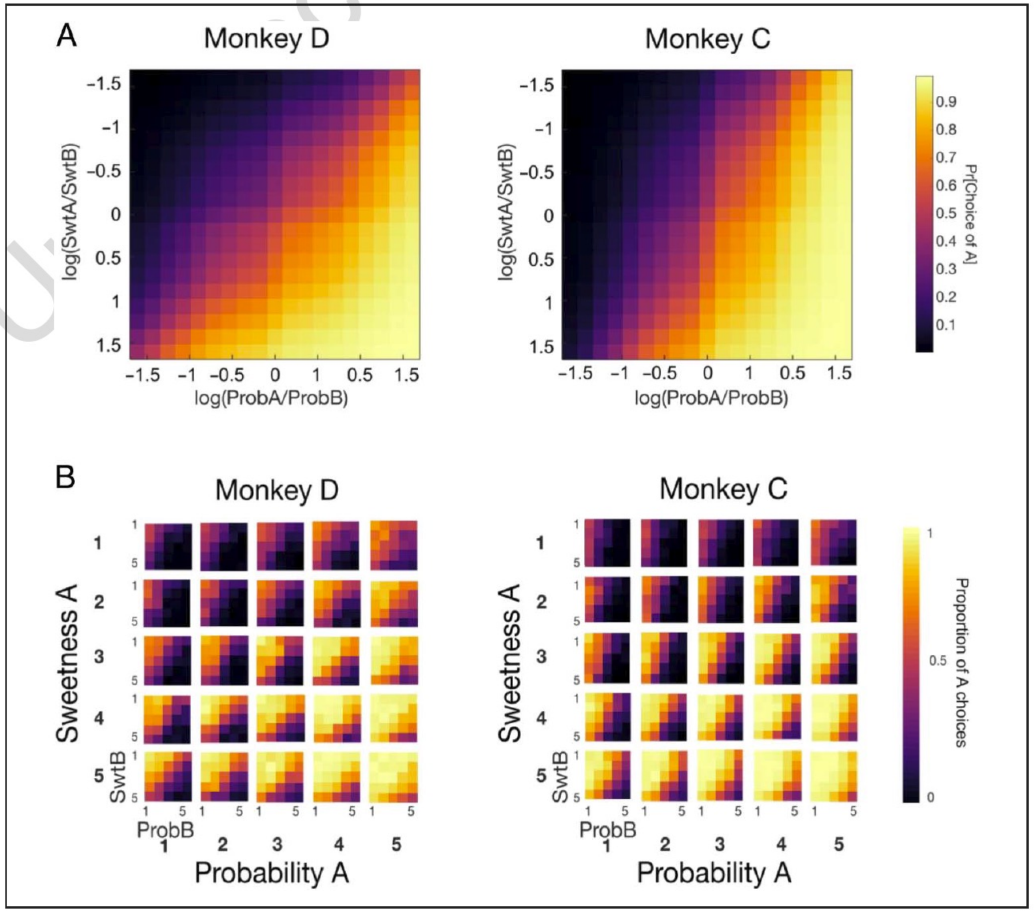
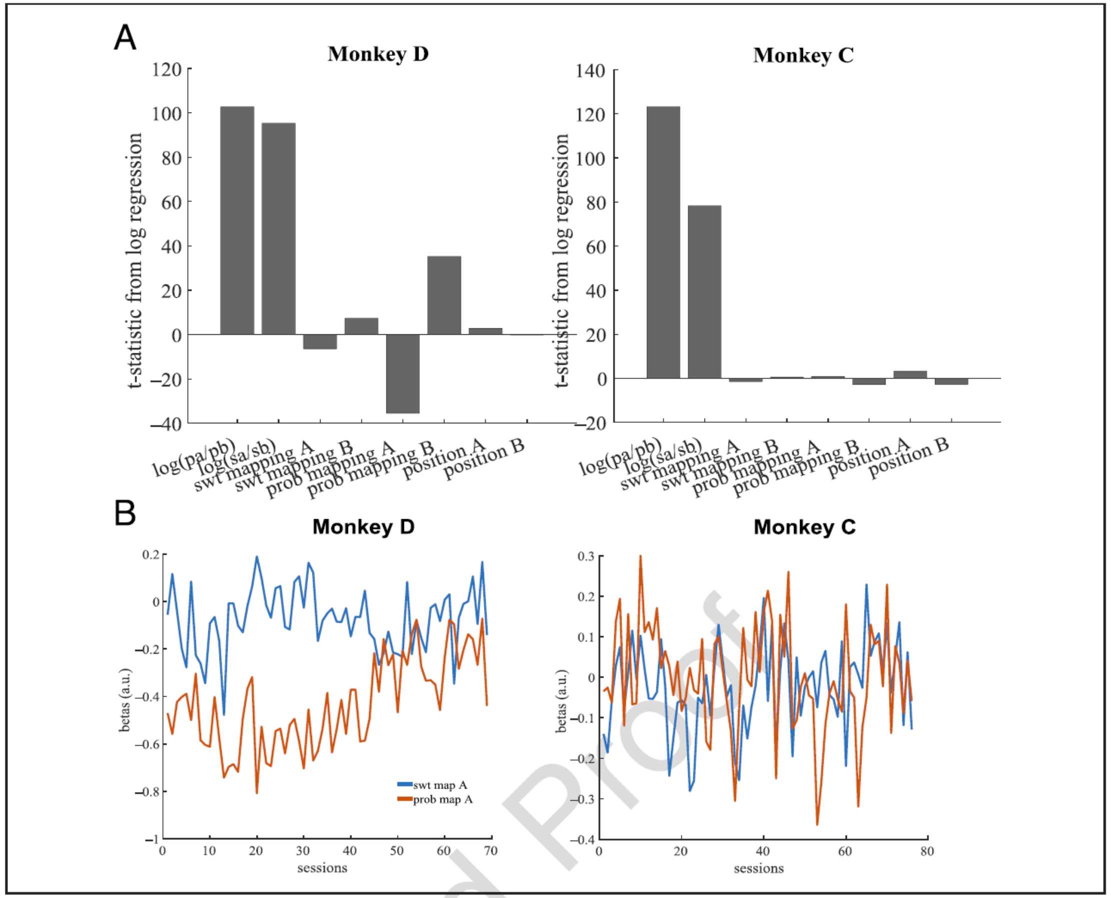
Appendix 1

Figure A1. Monkeys use multiple attributes to make choices. (A) Colormap of predicted choice probabilities from logistic regression on the log ratio of Sweetness A/B and Probability A/B (as in Figure 2D, but flattened; Equation 3). Brighter colors represent greater frequency with which arbitrary option A was selected. n = 57,082 (Monkey D) and 65,384 (Monkey C). (B) Colormaps of real choice frequencies. Each subplot shows choices when option A has sweetness magnitude of 1–5 (subplots from top to bottom, y axis) and probability magnitude of 1–5 (subplots left to right, x axis). Within each subplot, magnitudes of option B vary in the same range (1–5 for each). SwtB/ProbB = sweetness/probability of option B.



Appendix 2

Figure A2. Regression coefficients from logistic regressions on choice. (A) Regressions performed on concatenated data (Equation 1) found that the strongest predictors of choice are the relative magnitude of sweetness and probability of the two options. $n = 57{,}082$ (Monkey D) and 65,384 (Monkey C). (B) Plot of regression coefficients for sweetness/probability mapping from the choice regression over sessions. Only mapping betas for option A are shown, as betas for A and B are roughly inverses of each other. Across sessions, the relative weighting of direct versus indirect mapping varied considerably. Monkey D initially preferred indirect probability mappings, but this preference disappeared by the end of testing. Monkey C showed no consistent preference for direct or indirect mappings across testing.



Appendix 3

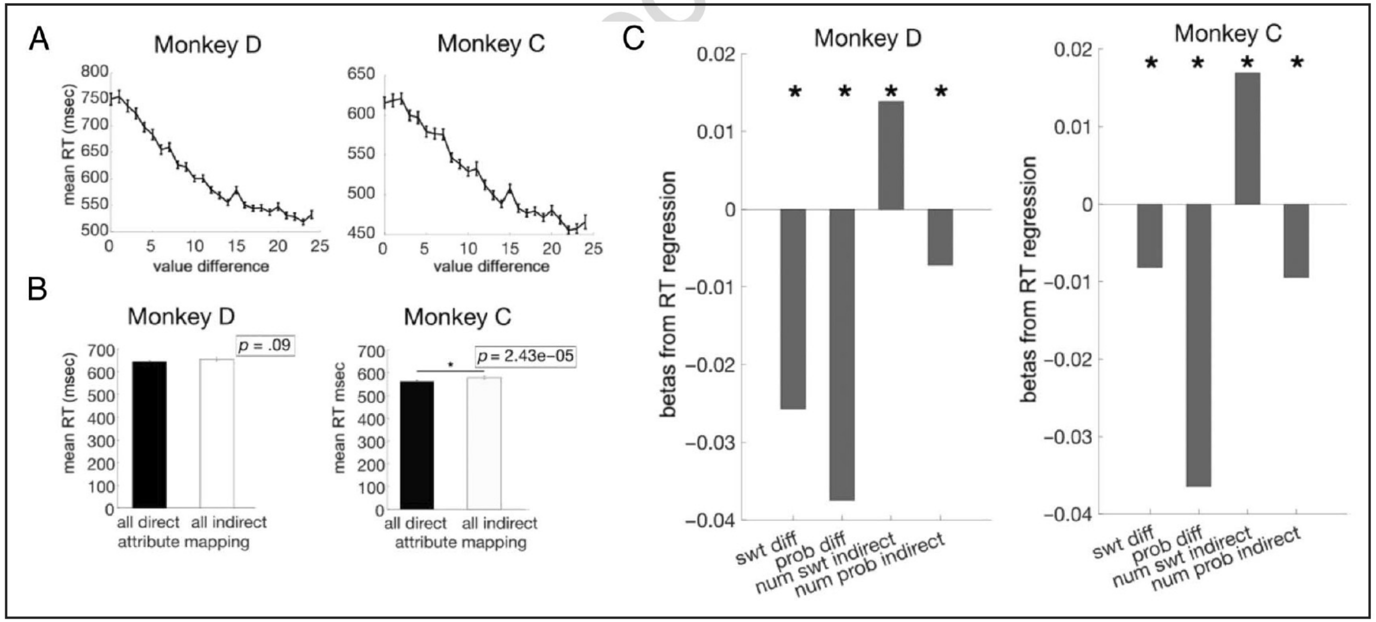


Figure A3. RTs in multiple attribute choices. RTs were defined as the time between the appearance of choice options on the screen and the time when the touch bar was released to select an option. Average RTs across sessions were 672.20 ± 30.5 msec for Monkey D and 570.31 ± 23.2 msec (95% CI) for Monkey C. RTs were shorter on trials with an objectively better option, compared to other trials, consistent with the idea that these are easier choices (Monkey D: 609.93 ± 11.68 msec [95% CI], Monkey C: 528.27 ± 10.33 msec [95% CI]; two-sample t tests: Monkey D: $p = 7.93 \times 10^{-27}$, Monkey C: $p = 8.29 \times 10^{-40}$). (A) Average RTs across sessions varied with the difference in the EV of the two options, defined as the Ordinal Sweetness × Ordinal Probability. Error bars indicate *SEM*. n = 69 (Monkey D) and 76 (Monkey C; sessions). (B) RTs were only weakly sensitive to direct/indirect attribute mapping in Monkey C (two-sample t test). Error bars indicate *SEM*. n = 69 (Monkey D) and 76 (Monkey C) sessions. (C) Regression coefficients from a linear regression on RT. SwtDiff and ProbDiff are the differences between the ordinal value of each attribute (0–4). NumSwtInd and NumProbInd are the number of indirect mappings of each attribute in the trial (0–2). $^*p < 0.01$. n = 56,889 (Monkey D) and 65,322 (Monkey C).

Appendix 4

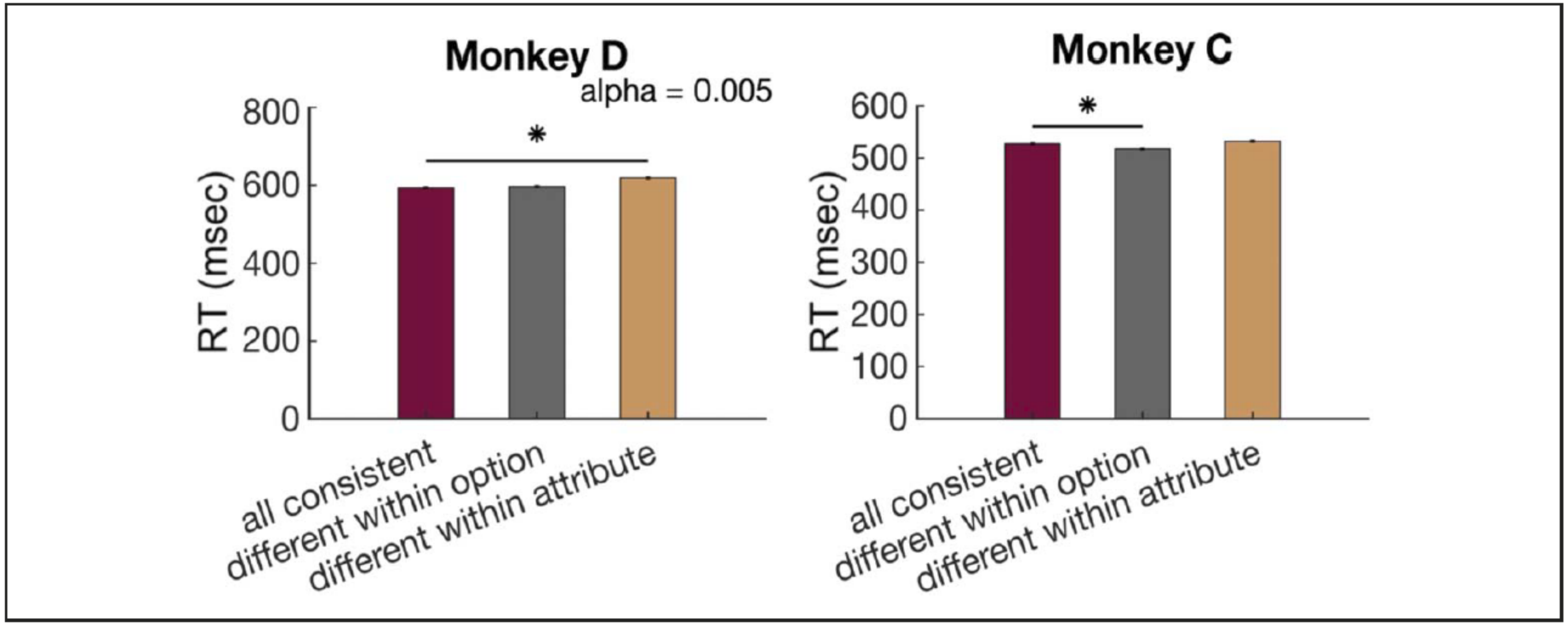


Figure A4. RTs split by attribute arrangement (as in Figure 2E). Error bars indicate *SEM*. Statistics were performed on log-transformed RTs. One-way ANOVA: Monkey D: $F(2, 10876) = 22.07, p = 2.71 \times 10^{-10}$; Monkey C: $F(2, 12586) = 14.11, p = 7.56 \times 10^{-7}$. Post hoc comparisons, $\alpha = .005$; Monkey D: all consistent versus different within option: $p = 0.98$, all consistent versus different within attribute: $p = 4.77 \times 10^{-9}$; Monkey C: all consistent versus different within option, $p = 2.92 \times 10^{-4}$, all consistent versus different within attribute, $p = .11$. Because of the sample size, some comparisons reached significance, but the effect size is very small and may reflect spurious effects.

Appendix 5

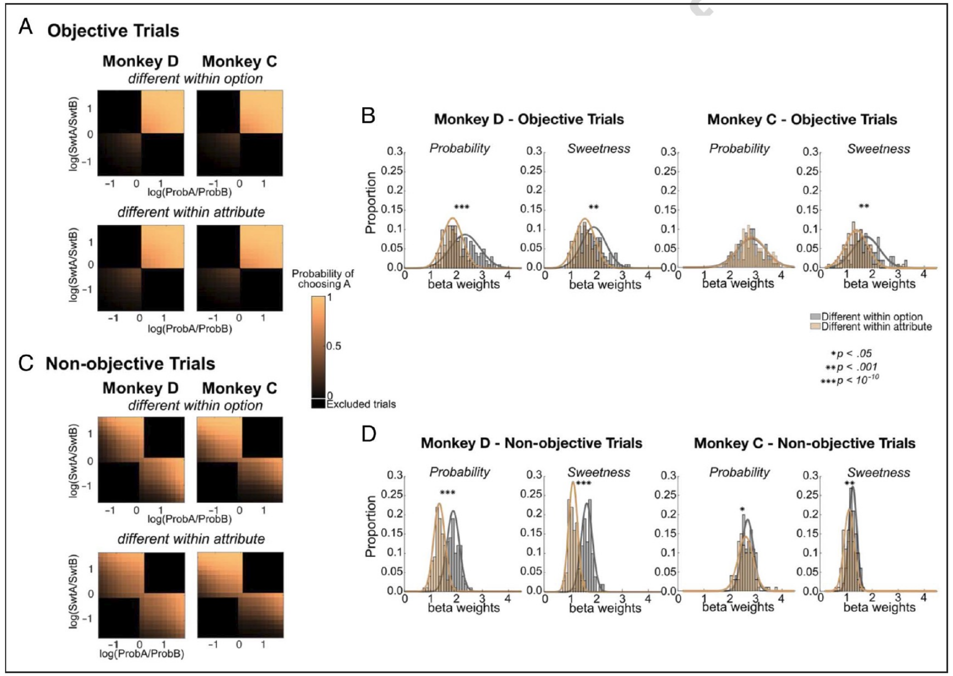
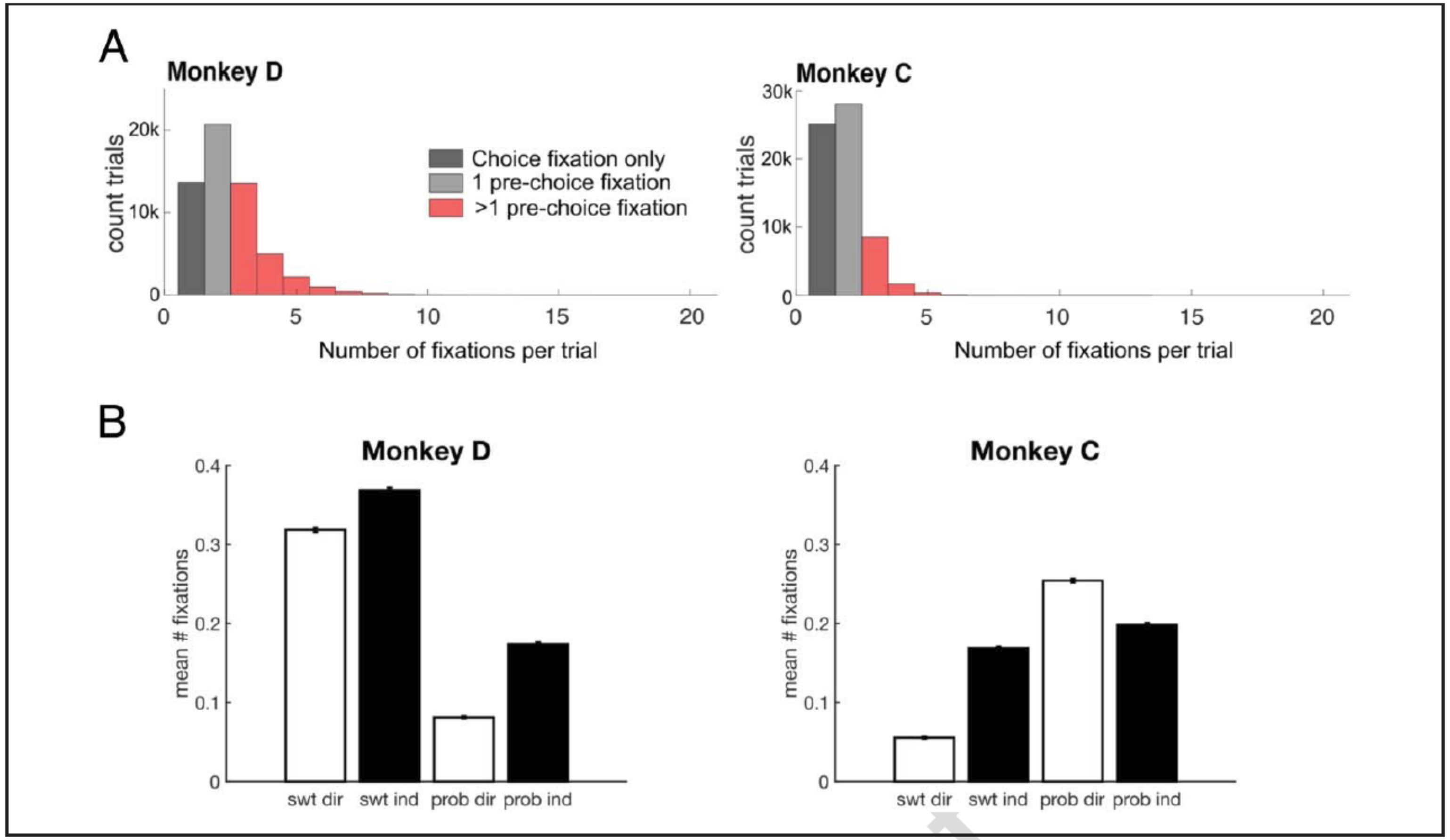


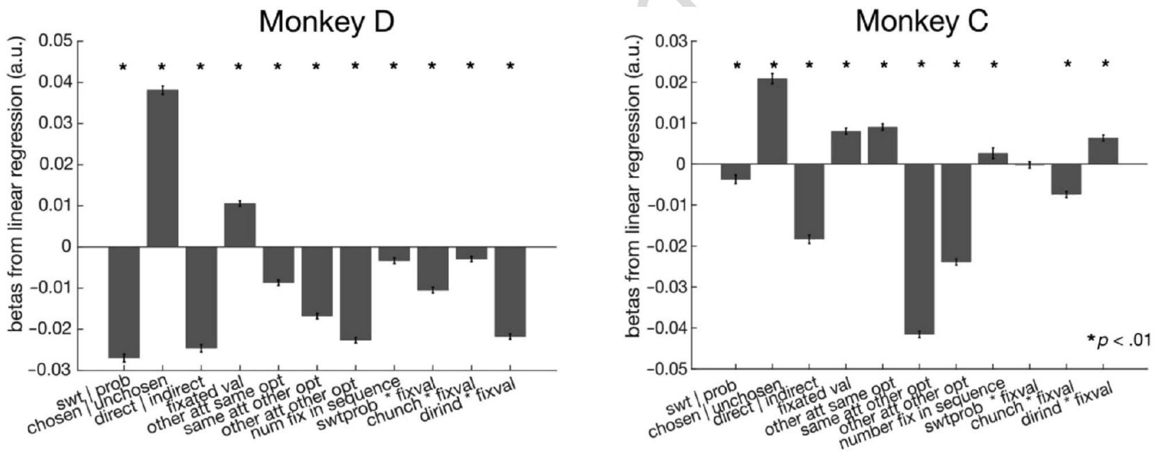
Figure A5. Choice models of objective and nonobjective trials. We compared trials with objectively better options ("Objective Trials") and those in which option A was better in one attribute and option B was better in the other ("Nonobjective Trials"). (A) Predicted probabilities from models fit to objective trials in which attributes were either mismatched within option (top) or within like attributes (bottom). Black regions indicate trials that were excluded because they did not meet the criteria of having one option superior to the other in both attributes. Monkey D: 18,207 included trials, Monkey C: 21,066 included trials. (B) Distributions of 100 bootstrapped samples of 400 trials, drawn from trials shown in A, in which attribute mappings were different within option (gray) or different within attribute (gold). Mismatched mappings within attribute consistently resulted in smaller slopes (i.e., more variable choices). (C) Predicted probabilities from models fit to nonobjective trials in which attributes were either mismatched within option (top) or within like attributes (bottom). Black regions indicate trials that were not included in the analysis because they did not meet these criteria. Monkey D: 38,875 included trials, Monkey C: 44,318 included trials. (D) Distributions of 100 bootstrapped samples of 400 trials, drawn from trials shown in C, separated as in B. Overall, there were slightly larger effects of attribute mapping on nonobjective trials, which may be more difficult for the monkey and therefore reveal choice inefficiencies to a greater extent. Importantly, all effects in any trial subset consistently showed that mismatched mappings within attribute resulted in smaller slopes (i.e., more variable choices). *Significant Wilcoxon rank-sum tests.

Appendix 6

Figure A6. Number of fixations on attribute bars within a trial. (A) Histogram of number of fixations per trial. Fixations that coincided with the choice (dark gray) were removed from all analyses. Trials with less than two fixations (light gray) were removed from analyses of prechoice gaze transitions. (B) Mean number of fixations per trial, split by direct/indirect mapping of each attribute. Fixations were counted between cue onset and choice. Error bars indicate *SEM*. n = 51,115 (Monkey D) and 53,727 (Monkey C) trials.



Appendix 7



Regressor	Description
swt | prob	Whether the fixation fell on a sweetness or probability bar (+1/–1)
chosen | unchosen	Whether the fixation fell on a bar in the chosen or unchosen option (+1/–1)
direct | indirect	Whether the fixation fell on a bar with direct or indirect mapping (+1/–1)
fixated val	Ordinal value of the fixated bar (1–5)
other att same opt	Ordinal value of the other attribute in the same option as the fixated bar (1–5)
same att other opt	Ordinal value of the same attribute as the fixated bar in the other option (1–5)
other att other opt	Ordinal value of the other attribute as the fixated bar in the other option (1–5)
num fix in sequence	The fixation number within a trial (1st, 2nd, etc.)
swtprob * fixval	Interaction of the swt | prob and fixated val regressors
chuch * fixval	Interaction of the chosen | unchosen and fixated val regressors
dirind * fixval	Interaction of the direct | indirect and fixated val regressors

Figure A7. Regression coefficients from multiple linear regressions. Regressions predicted fixation duration (log[msec]) from predictor variables on the *x* axis. $*p < .01$. Error bars show standard error of the coefficients. Ordinal values in the table are before mean centering. n = 81,158 (Monkey D) and 52,416 (Monkey C) fixations.

Thank you