Three gaps and what they mean for risk preference

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**Supplementary Material: Model competition (see figure 2).**

The heuristics can be separated into two categories: those that use only outcome information and ignore probabilities altogether (outcome heuristics) and those that use at least rudimentary probabilities (dual heuristics). In order to explain the policy of the heuristics, we borrow the token–type distinction from linguistics. In the present context, “types” are all distinct monetary outcomes per gamble. For instance, in the gamble offering -32 with a chance of 10%, the outcomes -32 and 0 are two types. “Token,” in contrast, refers to the actual instantiation of these two types in a sequence of, say, six draws: for instance, -32, 0, 0, 0, 0, -32 features six tokens (two of the type -32 and four of the type 0).

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| Heuristics  | Decision policy*Outcome heuristics* |
| Maximax (MAX) | Choose the gamble with the highest maximum type. |
| Minimax (MIN) | Choose the gamble with the highest minimum type.  |
| Equiprobable (EP) | Calculate the sum of all types within both gambles. Choose the gamble with the highest monetary sum. |
| Natural Mean (NM) | Calculate the natural mean of experienced tokens in both gambles by summing, separately for each one, all *n* experienced tokens and then dividing by *n*. Choose the gamble with the larger natural mean (i.e., the gamble with the best average outcome in the sampling phase). |
|  | *Dual heuristics* |
| Lexicographic (LEX) | Determine the most likely type of each gamble and their respective payoffs. Then select the gamble with the highest, most likely type. If both payoffs are equal, determine the second most likely type of each gamble, and select the gamble with the highest (second most likely) type. Proceed until a decision is reached. |
| Probable (P) | Determine the most likely type of each gamble. Then select the gamble with the highest, most likely type. If both types are equal, determine the second most likely type of each gamble, and select the gamble with the highest (second most likely) type. Proceed until a decision is reached.  |
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*Bayesian mean model (BM)*

The Bayesian mean model chooses the option with the higher average payoff, with types per gamble weighted by the subjective probability as determined by Bayesian updating of a uniform prior.

*Cumulative prospect theory (CPT)*

Cumulative prospect theory (Tversky & Kahneman, 1992) attaches decision weights to cumulated rather than single probabilities. The theory uses five adjustable parameters. Three parameters fit the shape of the value function; the other two fit the shape of the probability weighting function. The value function is

 (1)

where α+ and α‒ reflect the sensitivity to differences in positive (gains) and negative (losses) outcomes, respectively. The parameter λ in Equation 1 indicates the relative weight of gains and losses. It is assumed that a loss of a certain magnitude has a greater psychological impact on a choice than does a gain of the same magnitude.

Further, the probability *weighting function* is

, (2)

where the parameters γ+ and γ− govern the function’s curvature in the gain and loss domains, respectively, and indicate how sensitive choices are to differences in probability. Rather than fitting the CPT’s parameter to the data (giving it an advantage over the heuristics with no free parameters), we used three sets of parameter estimates from Erev, Roth, Slonim, & Barron (2002); Lopes and Oden (1999); and Tversky and Kahneman (1992). Based on these three sets of parameters, we arrived at three sets of choice predictions.

*Round-wise integration (RW)*

Round-wise integration (Hills & Hertwig, 2010; Wulff, Hills, & Hertwig, 2015) assumes that individuals compare the options across switches in the sequence of experienced tokens and tally the number of superior subsets of token average for each option. According to RW, decision makers prefer the option with the higher tally.

*Exemplar confusion model (ExCon)*

The exemplar confusion model (Hawkins, Camilleri, Heathcote, Newell, & Brown, 2014) assumes that with probability (1-*p*) each sample is accurately recorded in option-specific, limitless memory stores. However, with probability *p* a confusion process is activated that replaces the current sample with a value drawn at random from the unique values currently present in the option’s memory store. According to ExCon, decision makers prefer the option whose memory store has the highest average utility, assuming a risk-averse utility function based on Lopes and Oden (1999):

$$U=\frac{1}{N}\sum\_{i\in 1,…,N}^{}x\_{i}^{.551}.$$

**References**

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