



HAL
open science

Human Decision-Making beyond the Rational Decision Theory

Etienne Koechlin

► **To cite this version:**

Etienne Koechlin. Human Decision-Making beyond the Rational Decision Theory. Trends in Cognitive Sciences, 2020, 24, pp.4 - 6. 10.1016/j.tics.2019.11.001 . hal-03489029

HAL Id: hal-03489029

<https://hal.science/hal-03489029v1>

Submitted on 21 Jul 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Human-Decision-making beyond the Rational Decision Theory

by

Etienne Koechlin

Ecole Normale Supérieure, PSL Research University,

Université Pierre et Marie Curie,

Institut National de la Santé et de la Recherche Biomédicale,

Paris, France

Correspondence: etienne.koechlin@upmc.fr

Abstract

Two recent studies (Farashahi et al. and Rouault et al.) provide compelling evidence refuting the Subjective Expected Utility hypothesis as a ground model describing human decision-making. Together, these studies pave the way towards a new model that subsumes the notion of decision-making and adaptive behavior into a single account.

The Rational Decision Theory makes the core prediction that choices should maximize the Subjective Expected Utility (SEU) based on multiplying the subjective probability and value of choice outcomes [1, 2]. While in some specific, more or less complex circumstances, human choices admittedly violate this prediction, the SEU hypothesis has long been viewed as a ground model describing human decision-making. However, two studies published in 2019 (Rouault, Drugowitsch & Koechlin, *Nat Commun*[3]; Farashahi, Donahue, Hayden, Lee & Soltani, *Nat Hum Behav*[4]) provide the first compelling evidence refuting this idea and pave the way towards a new ground model of human decision-making.

Both studies investigated human and non-human primate decision-making in a very simple decision situation: namely choosing between two lotteries, each proposing a reward that will be potentially delivered after the choice. As in real-life, participants experienced and learned reward probabilities associated with each lottery along series of successive choices (**Fig. 1**). Through extensive and rigorous computational modeling and model fitting analyses, both studies show that participants' choices derived from the *additive* or *independent* contribution of (subjective) reward probabilities and values rather than from computing SEUs. Reward probabilities contributed more than reward values, indicating that humans prefer safer choices in agreement with the well-known risk-aversion effect [5]. Using neuroimaging, Rouault et al. further reveal that choice computations involved the dorsomedial prefrontal cortex, which activations indeed varied with these quantities independently. Farashahi et al. show that this independent contribution also hold in monkeys (who unlike humans, exhibited risk-seeking behavior), with further supporting evidence from neuronal recordings in the dorsolateral prefrontal cortex. The independent contribution is notably observed in a situation where SEUs are especially easy to compute, suggesting that the result generalizes to more complex situations, at least when reward probabilities are not explicitly provided to participants.

Farashahi et al. investigated the latter case by verbally instructing participants that one lotteries' attribute (e.g. their size) actually signaled their probability to deliver rewards. Interestingly, they report the opposite result: participants' choices reflected SEU computations rather than independent contributions. Farashahi et al. also trained monkeys to perform the same task but through extensive reinforcement learning. They observe monkeys' choices to reflect both SEU computations and independent contributions with roughly equal weights. In the monkey protocol, however, the training procedure applied to small samples of lotteries makes SEU quantities virtually identical to the values each lottery acquires through reinforcement learning. These reinforcement values indeed average the actual *experience of rewards* associated with each lottery and converge to SEUs [6]. Monkeys' choices thus appear to actually derive from the independent contribution of proposed

rewards' probabilities and values, along with lotteries' reinforcement values. Rouault et al.'s study confirms this interpretation: when participants were not verbally instructed about lotteries' probabilities, lotteries' reinforcement values encoded in the lateral orbitofrontal cortex were found to also contribute to their choices independently.

Thus, decision-making appears to conform with the SEU hypothesis only when reward probabilities are made explicit through verbal instructions. A possible interpretation is that verbal instructions induce participants to use their formal knowledge about probabilities to infer SEUs (remember that participants were university students). Both studies however report several additional key findings when lotteries' probability are not explicitly instructed, which support a more general, parsimonious and mechanistic view encompassing all these cases. Rouault et al. show that consistent with previous proposals[7], reward values independently contributed to choices through a normalization process that make them commensurable to reward probabilities. These authors further note that if these normalized quantities contributed to choices *with equal weights*, these choices would be similar to those deriving from SEU computations. We can accordingly reason that even in the verbally instructed condition, participants' choices might derive from an independent, equally weighted contribution of these quantities. Farashahi et al. report a finding that supports this hypothesis: the more volatile (or changing) the decision situation was, the less the probabilities' contribution was overweighed, *i.e.* the more probabilities and values tended to contribute to choices with equal weights. Moreover, the verbally instructed condition actually corresponds to an hyper volatile situation: when verbal instructions made lotteries' probabilities to be explicit, participants were *de facto* instructed that each trial differed and were unrelated to the preceding ones. Altogether, these findings lend weight to the idea that whatever the situation, human (and monkey) choices derive from the independent contribution of various subjective quantities including: the probabilities of prospective rewards, their values normalized across choice options and the options' reinforcement history, with relative weights adjusting to the volatility of the decision context.

This model is parsimonious as the relative weighting of these quantities might replace the need to consider multiple distortions of subjective compared to objective probabilities to make the SEU hypothesis consistent with human data in various contexts [8]. The model may reflect independent brain systems that concurrently influence choices or the valuation of choice options through the addition of multiple value components. As weighted sums may also be viewed as Lagrange functions [9], the model may also reflect that decision-making optimizes some quantities given some constraints (e.g. choose the safest option, unless the associated prospective reward is dramatically smaller). As the weighting depends upon the volatility of the environment[10], the model further bridges the notion of decision-making and adaptive behavior. Thus, both Farashahi et al. and Rouault et al.'s studies open the route for exciting future research to determine whether and how the model generalizes and adjusts the independent contribution to various uncertain and changing situations including multiple choice options and outcomes. Future research might notably establish the principles accounting for the efficiency of this adaptive decision model in real-life environments and for its evolution in primates. In other words, the principles that in real-life environments featuring uncertain, changing and open-ended situations, make this decision model more rational than the Rational Decision Theory.

References

1. Savage, L.J. (1954) The foundations of statistics, New-York Wiley.
2. Kahneman, D. and Tversky, A. (1979) Prospect theory: An analysis of decision under risk. *Econometrica* 47 (2), 263-91.
3. Rouault, M. et al. (2019) Prefrontal mechanisms combining rewards and beliefs in human decision-making. *Nat Commun* 10 (1), 301.
4. Farashahi, S. et al. (2019) Flexible combination of reward information across primates. *Nat Hum Behav*.
5. Kahneman, D. and Tversky, A. (1984) Choices, values, and frames. *American Psychologist* 39 (4), 341-50.

6. Sutton, R.S. and Barto, A.G. (1998) Reinforcement learning, The MIT Press.
7. Louie, K. et al. (2013) Normalization is a general neural mechanism for context-dependent decision making. *Proc Natl Acad Sci U S A* 110 (15), 6139-44.
8. Hertwig, R. and Erev, I. (2009) The description-experience gap in risky choice. *Trends Cogn Sci* 13 (12), 517-23.
9. Hoffmann, L.D. and Bradley, G.L. (2010) *Calculus for Business, Economics, and the Social and Life Sciences*, 10th edn., McGraw-Hill.
10. Behrens, T.E.J. et al. (2007) Learning the value of information in an uncertain world. *Nat Neurosci* 10 (9), 1214-1221.

Figure legend

Fig. 1. Prototypical decision contexts and predicted choice log-odds.

Left, subjects choose between two lotteries 1 and 2, each proposing a reward (R1 and R2) that will be delivered with distinct probabilities. Proposed rewards changed in every trials. After choosing, subjects do or don't receive the chosen, proposed reward. In experience-based uncertainty contexts, lotteries' probabilities (p and q) are unknown but remain constant over series of trials and subjects learned them by experience. In low and high volatile contexts, lotteries' probabilities change infrequently and frequently, respectively (here they swap between lotteries). In explicit, risky contexts, participants are verbally instructed that lotteries' probabilities are explicitly signaled along with proposed rewards. Similar to proposed rewards, lotteries' probabilities then change in every trial (hyper volatile context). **Right**, choice log-odds (logarithm of choice probability ratio for lottery 1 relative to 2) deriving from the Subjective Expected Utility, the independent contribution and the independent, normalized contribution model. The independent contribution model explains human and monkey choices in experience-based uncertainty context with higher weights on reward probabilities than values. Higher volatile contexts are associated with proportionally lower weights on probabilities. The Subjective Expected Utilities hypothesis explains human choices only in explicit, risky contexts by assuming subjective distortions of objective probabilities. The independent, normalized contribution hypothesis potentially explains human choices in all these contexts, provided that in explicit, risky contexts, reward probabilities and rewards contribute to choices with roughly equal weights (in which case the independent, normalized contribution is equivalent to the SEU hypothesis)(see [3] and [4] for details) .

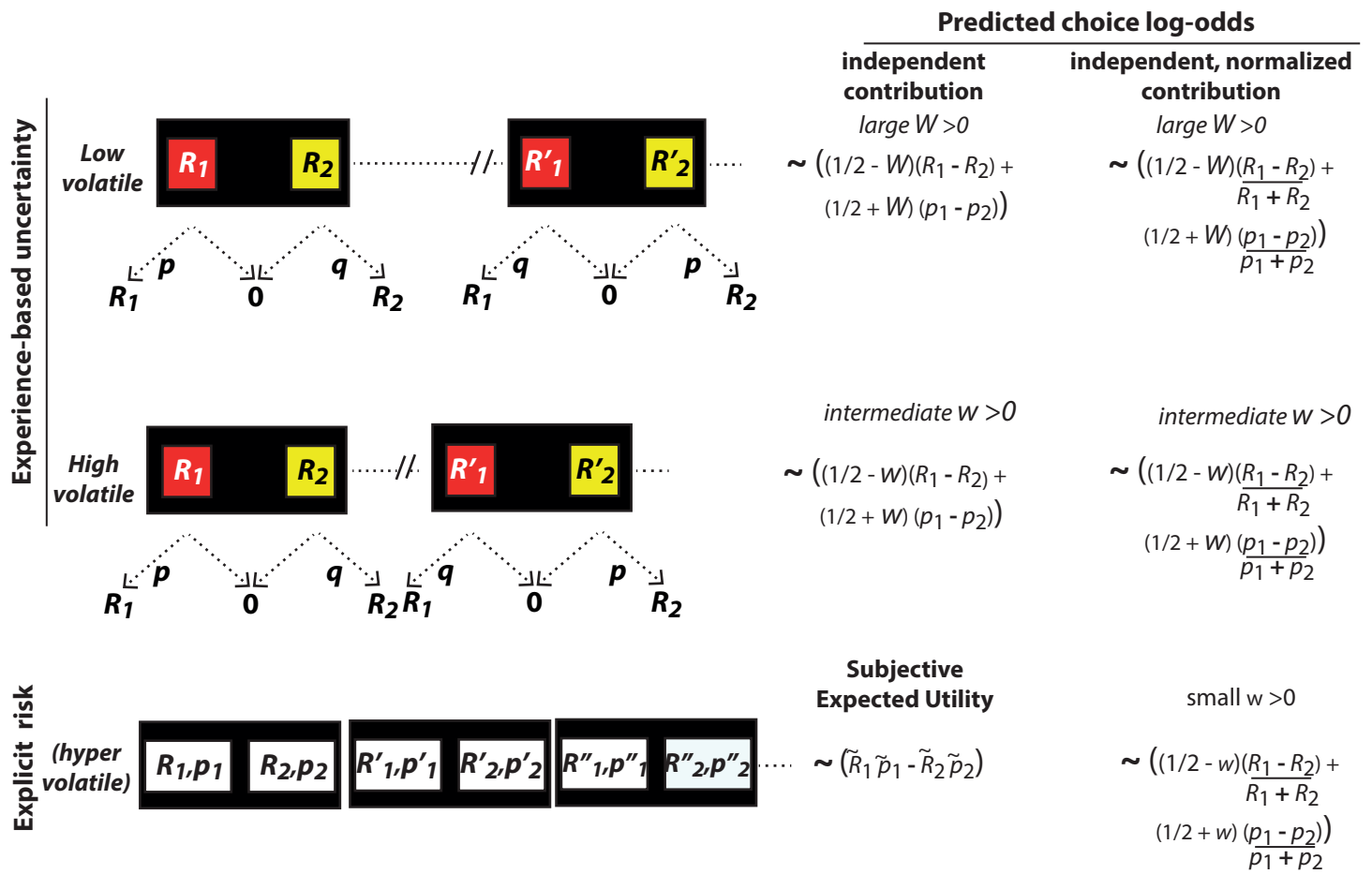


Fig. 1