Valuation Precision: from Behavioral Measures to Computational Modeling and Neural Underpinnings

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Abstract

Noise in value representations presents decision scientists with an identification problem. We measured trial-wise valuation precision using willingness-to-pay ranges for lotteries, where the range width indicates perceived valuation imprecision (uncertainty). Using a Bayesian inference model, we isolated distinct prior and likelihood components of valuation imprecision affecting the generation of value representations. Furthermore, upregulating norepinephrine and dopamine, but not acetylcholine increased valuation precision through these distinct components.

Keywords: Neuropharmacology; Risk-taking; Bayesian inference; Valuation; Dopamine

Introduction

Decision-making involves selecting the option with the highest estimated value. From a Bayesian perspective (Barretto-García et al., 2023; Khaw et al., 2021; Polanía et al., 2019; Woodford, 2020), an option with value ν elicits a noisy (neural) response r (measurement), drawn from a likelihood (probability) distribution $p(r|v)$. The brain computes a posterior by applying Bayes' rule, combining value encoding noise with prior beliefs about possible value distributions. Thus, valuation is inherently stochastic, involving estimates and precision. Both the prior—such as a bias toward high values or a wider spread of possible values—and the value encoding noise affect the value estimation.

Despite its importance, noise and its converse, precision, are hard to investigate and traditional methods failed to measure them within single trials. Additionally, while dopamine (DA), norepinephrine (NE), and acetylcholine (ACh) are theorized to reduce neural noise and improve precision in general (Parr & Friston, 2017; Yu & Dayan, 2005), causal relationships have yet to be established.

We addressed these gaps with a range-based valuation task measuring trial-wise precision and a Bayesian inference model isolating imprecision components. In a randomized, placebo-controlled, double-blind design, we tested how reboxetine (NE enhancer), methylphenidate (DA enhancer), and nicotine (ACh enhancer) affect value precision.

Methods

Range-based valuation task

In the range-based valuation task (Figure 1A), participants reported the minimum and maximum prices they were willing to pay (WTP) to play lotteries. The range—the difference between min and max WTP—directly measured perceived value precision, with wider ranges indicating greater imprecision. A modified Becker-DeGroot-Marschak procedure (Becker et al., 1964; Dost & Wilken, 2012; Wang et al., 2007) ensured truthful reporting. This task provided direct, reliable, and trial-wise measures of both subjective value and valuation imprecision.

Computational modeling

We assume that the noisy response r to an outcome's value follows a Gaussian distribution with mean ν (the true outcome value) and variance σ_{ν}^{2}. Because value is a magnitude variable, we allow the noise to increase with value, modeled as: $\sigma_{\nu}^{2} = S * v + B$, where S and B are individual-specific free parameters. Higher S implies more noise at higher values, while a higher B indicates greater overall noise in the (neuronal) value encoding.

The decision maker infers the value of each outcome by computing the posterior of the true value through Bayesian inference $p(v|r) \propto p(v_0)p(r|v)$. The prior $p(v_0)$ is assumed to be a Gaussian distribution with individual-specific mean μ_0 and variance σ_{μ}^{2}.

Critically, the model assumes that decision makers first independently infer the value of each outcome v_1 and v_2 of a lottery with two possible outcomes, leading to two posterior distributions (Figure 1B). Then they combine the two posteriors distributions as a mixture distribution $q_1 p(v_1|r_1) + q_2 p(v_2|r_2)$, where q_1 and q_2 are the

probabilities associated with each outcome (Figure 1C). The mean of this mixture distribution (μ_{mix}) is the WTP (subjective value) of the lottery. The max and min WTP participants actually reported in our task correspond to the WTP plus and minus the uncertainty (standard deviation) of the mixture distribution,

Moreover, the reported WTP range (the difference between max and min WTP) can be viewed as a confidence interval (CI): $\mu_{mix} \pm C * \sigma_{mix}$, in which C is a free scaling factor, a threshold relating the uncertainty of the mixture distribution to the range participants actually report. Some participants might be more conservative, reporting 95% CIs, while others might be less conservative, reporting 60% CIs. Response noise is a free parameter σ_R. Therefore, our model can decompose reported value imprecision into value representation (affected by prior and value encoding noise) and response tendencies (threshold and response noise), allowing us to test how different neuromodulators affect these distinct processes.

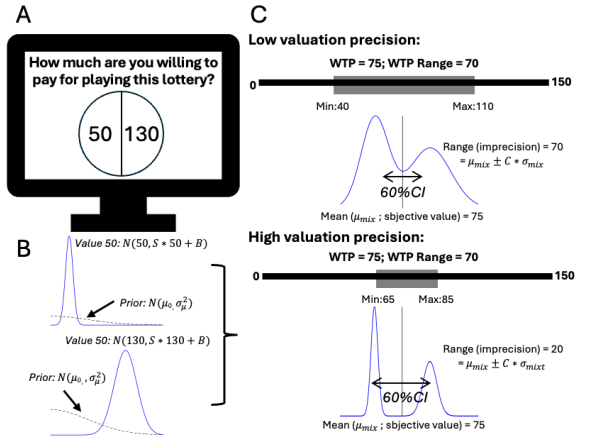

Figure 1: Range-based valuation task and valuation imprecision. Participants reported the min and max prices they are willing to pay for a lottery (e.g., 50% chance of 50 points, 50% chance of 130 points). This method captures both subjective value and valuation uncertainty. Example posterior distributions: low precision range, 40-110 points (mean WTP of 75, imprecision of 70); high precision range, 65-85 points (same mean, imprecision of 20). In the Bayesian model, prior $N(\mu_0, \sigma_\mu^2)$, value encoding noise ($\sigma_v^2 = S * v + B$) and decision threshold C are estimated for each individual. Noisier value representations and higher thresholds lead to wider reported ranges.

Results and Discussion

The range-based valuation task was validated in Experiment 1(N=25): reported WTP was higher for lotteries with higher expected value, WTP from the traditional point-based method matched that of the range-based method, WTP variability was higher for lotteries with larger ranges, and the WTP range was negatively correlated with confidence (Figure 2A).

To test if psychoactive substances reduce perceived valuation imprecision, in Experiment 2, participants received 4 mg reboxetine, 20 mg methylphenidate, 2 mg nicotine, or placebo, with 40 participants per group. We used a Bayesian regression model on 157 participants. We fitted Bayesian inference models individually, and our model fitted the data well (Figure 2B). Moreover, both methylphenidate (MPH; BF = 56.55) and reboxetine (RBX; BF = 19.3) reduced WTP range compared to placebo (Figure 2C). Modeling revealed that MPH reduced prior mean (BF = 20.86), and tended to reduce the decision threshold C (BF = 16.28). By contrast, RBX reduced both prior variance (BF = 73.77) and the value encoding nois B (BF = 26.97). Together, these findings suggest that DA and NE increase valuation precision (perceived certainty) through different mechanisms: DA lowered the conservative decision criterion, becoming more certain overall across noise conditions, while NE reduces overall noise in value representation.

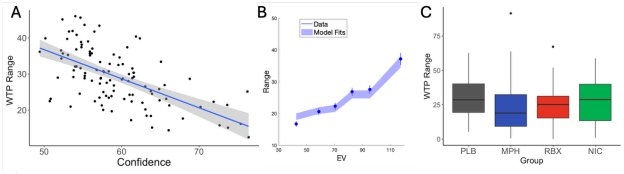

Figure 2: A. WTP range (perceived valuation imprecision) was negatively correlated with reported confidence. B. WTP range was higher for lotteries with higher EV, a pattern captured by our Bayesian inference model. C. WTP range across drug groups. The line inside each box represents the median, and the box limits denote the 25th and 75th percentiles.

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References

Barretto-García, M., de Hollander, G., Grueschow, M., Polanía, R., Woodford, M., & Ruff, C. C. (2023). Individual risk attitudes arise from noise in neurocognitive magnitude representations. Nature Human Behaviour, 7(9), 1551–1567. https://doi.org/10.1038/s41562-023-01643-4

Becker, G. M., Degroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. Behavioral Science, 9(3), 226–232. https://doi.org/10.1002/bs.3830090304

Dost, F., & Wilken, R. (2012). Measuring willingness to pay as a range, revisited: When should we care? International Journal of Research in Marketing, 29(2), 148–166. https://linkinghub.elsevier.com/retrieve/pii/S0167811612000067

Khaw, M. W., Li, Z., & Woodford, M. (2021). Cognitive Imprecision and Small-Stakes Risk Aversion. The Review of Economic Studies, 88(4), 1979–2013. https://doi.org/10.1093/restud/rdaa044

Parr, T., & Friston, K. J. (2017). Uncertainty, epistemics and active inference. Journal of The Royal Society Interface, 14(136), 20170376. https://doi.org/10.1098/rsif.2017.0376

Polanía, R., Woodford, M., & Ruff, C. C. (2019). Efficient coding of subjective value. Nature Neuroscience, 22(1), 134–142. https://doi.org/10.1038/s41593-018-0292-0

Wang, T., Venkatesh, R., & Chatterjee, R. (2007). Reservation Price as a Range: An Incentive-Compatible Measurement Approach. Journal of Marketing Research, 44(2), 200–213. https://doi.org/10.1509/jmkr.44.2.200

Woodford, M. (2020). Modeling Imprecision in Perception, Valuation, and Choice. Annual Review of Economics, 12(1), 579–601. https://doi.org/10.1146/annurev-economics-102819-040518

Yu, A. J., & Dayan, P. (2005). Uncertainty, Neuromodulation, and Attention. Neuron, 46(4), 681–692. https://doi.org/10.1016/j.neuron.2005.04.026