Signatures proposed to index perceptual effects emerge in a purely cognitive task

Sixing Chen[1], Dobromir Rahnev[2]

[1]Department of Psychology, New York University, New York, NY, USA

[2]School of Psychology, Georgia Institute of Technology, Atlanta, GA, USA

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Correspondence

Sixing Chen

New York University

6 Washington Place

New York, NY, 10003, USA

E-mail: sixing.chen@nyu.edu

Abstract

A central question in many studies on perception and consciousness is whether the effects of a given manipulation are perceptual or cognitive. Typically, studies seek to find evidence that the raw sensory experience has been altered, that is, a manipulation produces perceptual rather than cognitive effects. There are two major proposals for behavioral signatures that could allow this type of inference. First, a long-standing proposition is that different parameters of the drift diffusion model (DDM) map onto different effects, such that a drift rate bias indicates a perceptual effect, whereas a starting point shift indicates a cognitive effect. Second, a newer proposal holds that, when plotted as a function of a sensory feature, changes in the peak of the distributions for confidence and reaction time (RT) imply that a given manipulation's effects are perceptual. Here we test both of these proposals. We designed a purely cognitive task where no effects can be perceptual, and examined whether the proposed signatures of perceptual effects occur in this task. Participants viewed numbers generated by two distributions and indicated which distribution the numbers likely came from. In separate conditions we manipulated prior beliefs and rewards related to each distribution. We found that both of these manipulations elicited the same signatures previously proposed as indicative of purely perceptual effects. Our results demonstrate that individual DDM parameters and the peaks of confidence and RT distributions in isolation are insufficient to distinguish between perceptual and cognitive effects.

1. Introduction

Perceptual decision making is sensitive to external manipulations. Many manipulations appear to impact perception by altering raw sensory experience. For example, in the well-known Müller-Lyer illusion (Müller-Lyer, 1889), adding flanked arrowheads to lines changes our perception of the length of the lines. However, other manipulations, such as providing unequal rewards or expectations for different stimulus categories could possibly act via either perceptual or cognitive changes (or both) (Alilović et al., 2019; Bang & Rahnev, 2017; Kok et al., 2013; Rungratsameetaweemana et al., 2018; Rungratsameetaweemana & Serences, 2019). The question of whether a given effect is perceptual or cognitive has important implications for many studies of perception and consciousness, and has been central in several recent debates in the field (Abid, 2019; Denison et al., 2018; Knotts et al., 2020; Lee et al., 2023; Rahnev et al., 2011). Given the significance of distinguishing between perceptual or cognitive effects, developing methods for determining the mechanisms through which a given manipulation affects perceptual judgments is of utmost importance.

Two methods have been proposed that promise to allow the determination of whether a given manipulation has perceptual or cognitive effects. First, it has been proposed that changes in different drift-diffusion model (DDM) parameters can be used to distinguish between perceptual and cognitive effects. Specifically, if a manipulation results in a drift rate bias, then it can be assumed to have perceptual effects, whereas if it results in a starting point shift, then it can be assumed to have cognitive effects (Germar et al., 2014; Voss et al., 2008). For example, expecting that a stimulus would come from a given category could either bias the drift rate towards values that favor that category or shift the starting point of the accumulation towards that category (Figure 1A). Therefore, according to this proposal, examining how a given manipulation affects the DDM fits allows the researcher to infer whether the manipulation acts via perceptual or cognitive mechanisms. Note that this proposal was recently examined by Sánchez-Fuenzalida et al. (2022) who found that while DDM fits have a diagnostic value for distinguishing between perceptual and cognitive effects, there is no one-to-one mapping between the individual parameters and the type of effect obtained. We return to this work in the Discussion.

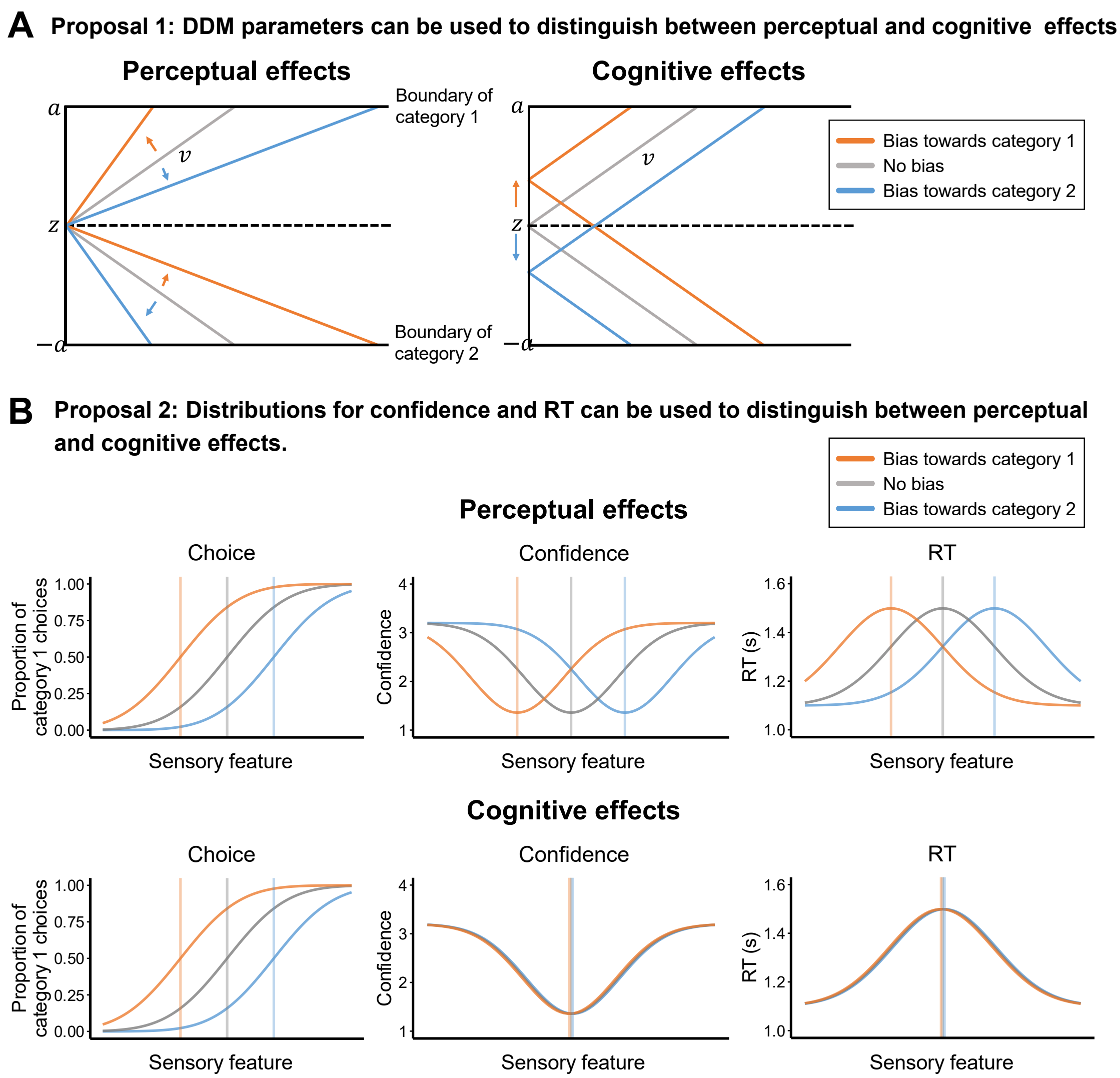


Figure 1. Proposed signatures to distinguish between perceptual and cognitive effects. (A) The first proposal holds that cognitive effects map onto a shift of the starting point of accumulation, while perceptual effects map onto drift rate bias towards either category. (B) The second proposal holds that while both perceptual and cognitive effects alter choices, only perceptual effects lead to shifts in the peaks of the confidence and RT distributions. Specifically, perceptual effects are proposed to shift the sensory feature value with maximum uncertainty (corresponding to the sensory feature value with lowest confidence and highest RT). In contrast, cognitive effects are proposed not to change confidence and RT distributions.

Another proposal holds that examining the distributions for confidence and reaction time (RT) allows the determination of whether a given manipulation's effects are perceptual or cognitive (Gallagher et al., 2019, 2021; Maldonado Moscoso et al., 2020). For this method to be applicable, the experiment needs to include a range of feature values (e.g., stimulus orientation) that allows a researcher to plot the distribution for confidence and RT as a function of feature value separately for each manipulation. Shifts in the peaks of the confidence and RT distributions can then be interpreted as indicating perceptual effects, whereas a lack of shifts in the peaks of the distributions for confidence and RT indicates cognitive effects (Figure 1B). Note that in both cases there are identical shifts in the sigmoid functions that describe the relationship between the sensory feature and choice.

Here, we test these proposals by examining the effects of prior and reward manipulation in a purely cognitive task. The idea is to use a task where all effects can only be cognitive in nature and examine whether the DDM fits and peaks of the confidence and RT distributions behave as would be expected for cognitive (rather than perceptual) effects. In three experiments, participants judged whether a number presented on the screen came from one of two underlying distributions (with different means). We found that both signatures previously proposed to index perceptual effects emerged naturally in our purely cognitive task, demonstrating that these signatures cannot automatically be interpreted as indicating a perceptual effect.

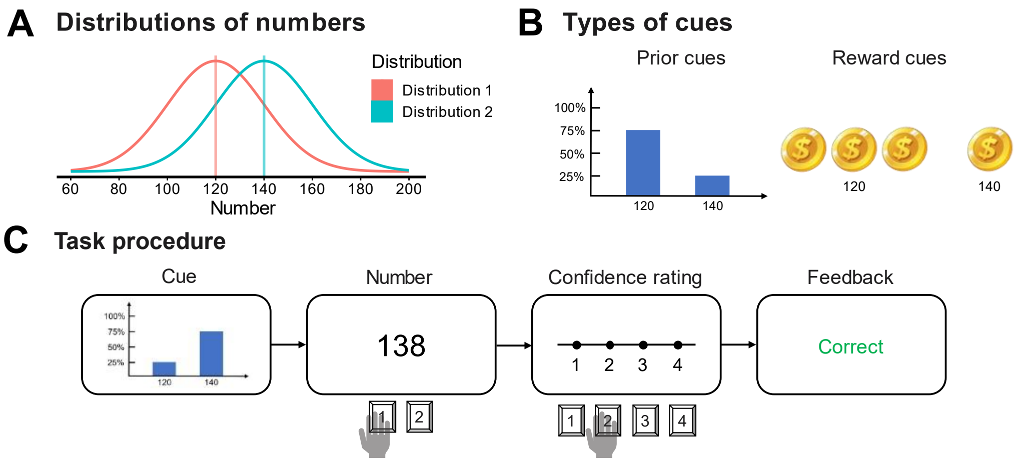
2. Materials and Methods

2.1. Participants

Participants in all three experiments were adults recruited on Prolific. 85 participants in total (20 females, mean age = 30.7 years, SD = 8.2 years) participated in the study. Exp 1 had 21 participants, Exp 2 had 32 participants, and Exp 3 had 32 participants. Each participant performed only one experiment. Participants provided informed consent before the study and were compensated $8.63 per hour as basis and about $2 as bonus. The exact bonus participants got depended on their task performance. Every 4 points they earned in the tasks would convert to 1 cent as bonus. Each experiment took about 75 minutes.

2.2. Procedure

In all three experiments, participants were presented with an integer (e.g., 138), which was randomly generated from one of the two Gaussian distributions: distribution 1 (mean = 120, SD = 20) and distribution 2 (mean = 140, SD = 20; Figure 2A). Participants indicated which distribution generated the integer by pressing “1” or “2” on the keyboard (Figure 2C). After making the decision, participants rated their confidence about the accuracy of the decision on a 4-point scale by pressing “1”, “2”, “3”, or “4” on the keyboard (“1” = low confidence, “4” = high confidence). Both decision stage and confidence rating stage were untimed. After the confidence rating, participants received feedback about the correctness of the decision ("Correct” or “Wrong”, 500 ms). The inter-trial interval was 500 ms.



D Experimental conditions

Experiment	Prior manipulation	Reward manipulation	trials/manipulation
Experiment 1	75/25, 50/50, 25/75	3/1, 2/2, 1/3	384
Experiment 2	75/25, 50/50, 25/75	-	768
Experiment 3	-	5/1, 2/2, 1/5	768

Figure 2. Task procedure. (A) Probability distributions of presented numbers. Participants were presented with integers generated randomly by one of the two Gaussian distributions: distribution 1 ($\mu = 120, \sigma = 20$) or distribution 2 ($\mu = 140, \sigma = 20$). (B) Types of cues. Participants saw cues of two different types. Prior cues contained information about which distribution was more likely to generate the ingeter. Reward cues contained information about which distribution would be rewarded more. (C) Task procedure. Participants indicated which of two distributions generated an integer and provided a confidence rating on a 4-point scale. Each trial began with a cue that provided informaiton about either the prior probability of each distribution or the reward associated with each distribution. (D) Experimental conditions in the three experiments. Exp 1 contained both prior and reward manipulations, Exp 2 contained only prior manipulation, and Exp 3 contatined only reward manipulation. Ratios under prior manipulation are probabilitiy ratios of the two distribution informed by prior cues (e.g., 75/25 means distribution 1 was 3 times more likely), whereas ratios under reward manipulations are reward ratios of the two distributions informed by reward cues (e.g., 1/5 means distribution 2 would be rewarded 5 times more).

At the beginning of each trial, participants were first presented with a cue (500 ms), which provided information about the following integer and thus might bias the subsequent decision. The cues had two different types, corresponding to two different manipulations: prior manipulation and reward manipulation (Figure 2B). Exp 1 contained both manipulations, Exp 2 contained only prior manipulation, and

Exp 3 contained only reward manipulation. Each type of cue had three levels. The prior manipulation cues informed participants that distribution 1 was 3 times more likely (distribution 1 cue), two distributions were equally likely (neutral cue), or distribution 2 was 3 times more likely (distribution 2 cue). In the prior manipulation condition, a correct decision would be rewarded 2 points. The reward manipulation cues in Exp 1 informed participants that distribution 1 would be rewarded 3 times more (distribution 1 cue), two distributions would be equally rewarded (neutral cue), or distribution 2 would be rewarded 3 times more (distribution 2 cue). In Exp 3, we changed the reward ratio of cues from 3 times more to 5 times more to match the impact of prior manipulation in Exp 2. In the reward manipulation condition in Exp 1, a correct decision would be rewarded 3 points (5 points in Exp 3) under distribution 1 cues or distribution 2 cues, and 2 points under neutral cues, while the two distributions did not differ in how likely they generated the integers (Figure 2D).

In all three experiments, participants completed 16 blocks, with each consisting of 48 trials (for a total of 768 trials; Figure 2D). In Exp 1, manipulations were block-designed. Prior manipulation and reward manipulation each consisted of 8 blocks, and blocks from the two manipulations were conducted by turns. Blocks in Exp 2 and Exp 3 consisted of either only prior manipulation trials or only reward manipulation trials. Participants were given 30s breaks between blocks. Before each block started, participants were informed of the total points they had accumulated and the number of remaining blocks. All three experiments were coded in Python using PsychoPy (Version 2021.2.3) and were conducted online on Pavlovia (Peirce, 2007).

2.3. Analyses

For each participant in each of the three experiments, we excluded trials with RTs outside mean ± 3 × *SD*s or larger than 6 s before conducting any data analyses.

2.3.1. *Drift-diffusion model analyses*

We conducted drift-diffusion model analyses using the hierarchical drift-diffusion model (HDDM) toolbox (Wiecki et al., 2013). We fitted models to the RT distributions from individual participants separately with Markov chain Monte Carlo sampling (2000 samples; burn-in = 200 samples) to get posterior distributions of parameters, and computed posterior means of the drift criterion δ and the starting point z as the estimations of drift-rate bias and starting point for each participant. Note that the drift criterion δ (bias of drift rate towards a certain distribution) and the drift rate v are separate free parameters. When stimulus from distribution 2 are presented, the actual drift rate is $v + \delta$, whereas when stimulus from distribution 1 are presented, the actual drift rate is $-v + \delta$. We also set the decision boundary to a for distribution 2 and $-a$ for distribution 1 so that the midpoint between the two boundaries is 0. To test the effects of cues and manipulations on model parameters, we allowed the drift criterion δ and the starting point z to vary between different cues and manipulations in Exp 1 while keeping other parameters fixed across conditions. In Exp 2 and Exp 3 which contained only one type of manipulation, we allowed both parameters to vary between different cues. To test the effects of prior manipulation and reward manipulation on DDM parameters, we performed paired-sample t-tests comparing drift-criterion and starting point z between different cues.

2.3.2. *Choice, confidence, and RT analyses*

To investigate how prior manipulation and reward manipulation impacted choice, confidence, and RT, we examined the relationships between numbers and the three indexes under different manipulations and cues. For choice, we fitted a cumulative normal distribution function $\Phi(\mu, \sigma^2)$ with mean μ and standard deviation σ to the function that plots the probability of choosing distribution 2 as a function of the number presented. The fitting was done for each cue (D1, N, and D2) separately using maximum likelihood estimation. Parameter boundaries were $[60, 200]$ for μ and $[15, 60]$ for σ. For confidence and RT, we fit raised Gaussian functions $a \times \phi(\mu, \sigma^2) + b$, where μ is the mean, σ is and standard deviation, b is a parameter that "raises" the distribution so that it converges to b (rather than 0) when extended to $-\infty$ or ∞, and a is a parameter that "stretches" the height of the distribution to match the units of the confidence and RT data. We estimated the parameters by minimizing the sum of squared error between predictions and data: $\sum_i \left(\text{Confidence}_i - \text{Confidence}_{\text{pred},i}\right)^2$ and $\sum_i \left(\text{RT}_i - \text{RT}_{\text{pred},i}\right)^2$, where i is the trial index. For confidence fitting, parameter boundaries were $[60, 200]$ for μ, $[5, 200]$ for σ, $[-10, -2000]$ for a, and $[-5, 15]$ for b. For RT fitting, parameter boundaries were $[0, 260]$ for μ, $[5, 600]$ for σ, $[1, 2000]$ for a, and $[-10, 10]$ for b. Due to the fact that more uncertain choices are accompanied by lower confidence and higher RT, the parameter a used to stretch the height of distributions were positive in the confidence fitting and negative in the RT fitting. We used raw data (i.e., exact stimulus numbers) to fit the curves throughout the fitting process, while we plotted empirical data by binning numbers in bins of 10 for visualization purposes.

We then used μ fitted from the three indexes to analyze the impacts of manipulations and cues. In choice fitting, μ is the point of subjective equality (PSE). In confidence and RT fitting, μ is the peak confidence or RT plotted as a function of number. Thus, μ can reflex biases in the three indexes. We performed paired-sample t-tests comparing μ between different cues separately for choice, confidence, and RT in each experiment to determine the effects of cues on the indexes. P-values for pair-sample t-tests were corrected with Bonferroni corrections.

2.4. Data and code

All data and code are available at https://osf.io/k6nt8/.

3. Results

We investigated whether (1) DDM parameter fits and (2) the peaks of confidence and RT distributions can be used to distinguish between perceptual and cognitive effects in perceptual decision-making. To do so, we tested how prior and reward manipulations impacted DDM parameters and confidence/RT distribution peaks in a purely cognitive task to see whether signatures previously associated with perceptual effects could emerge naturally in our purely cognitive task. Participants judged whether a number displayed on the screen was more likely to come from a Gaussian distribution with a low mean ($\mu = 120, \sigma = 20$; Distribution 1) or a high mean ($\mu = 140, \sigma = 20$; Distribution 2). We performed three experiments. In Exp 1, on each trial participants saw a prior cue that predicted the true distribution or a reward cue that gave higher payoff for correctly choosing one of the distributions. Exp 2 and Exp 3 included only prior and reward cues, respectively, but had higher number of trials for each manipulation (Figure 2D).

3.1. Manipulation checks

We first examined the effectiveness of the prior and reward manipulations in the three experiments. We found that participants' choices were significantly altered by both prior and reward cues. Specifically, the proportion of distribution 2 choices was highest for prior cues that favored distribution 2 (i.e., D2 cues; 77.6% in Exp 1; 75.7% in Exp 2), lowest for prior cues that favored distribution 1 (i.e., D1 cues; 23.3% in Exp 1; 25.5% in Exp 2), and in-between for neutral cues (i.e., N cues; 52.1% in Exp 1; 51.2% in Exp 2) with these difference being highly significant (Exp 1:

$F(2,40) = 176.78$, $p = 1.4\times10^{-20}$; Exp 2: $F(2,62) = 220.13$, $p = 6.8\times10^{-29}$; Figure 3). We observed the same outcomes but with smaller effect sizes for the reward manipulation with distribution 2 being chosen most often for D2 reward cues (59.6% in Exp 1; 59.6% in Exp 3), least often for D1 reward cues (41.6% in Exp 1; 42.6% in Exp 3), and in-between for neutral cues (i.e., N cues; 53.2% in Exp 1; 53.1% in Exp 3), with these differences being again significant (Exp 1: $F(2,40) = 22.80$, $p = 2.5\times10^{-7}$; Exp 3: $F(2,62) = 23.25$, $p = 2.9\times10^{-8}$). These results indicate that both manipulations were effective in biasing participants' choices.

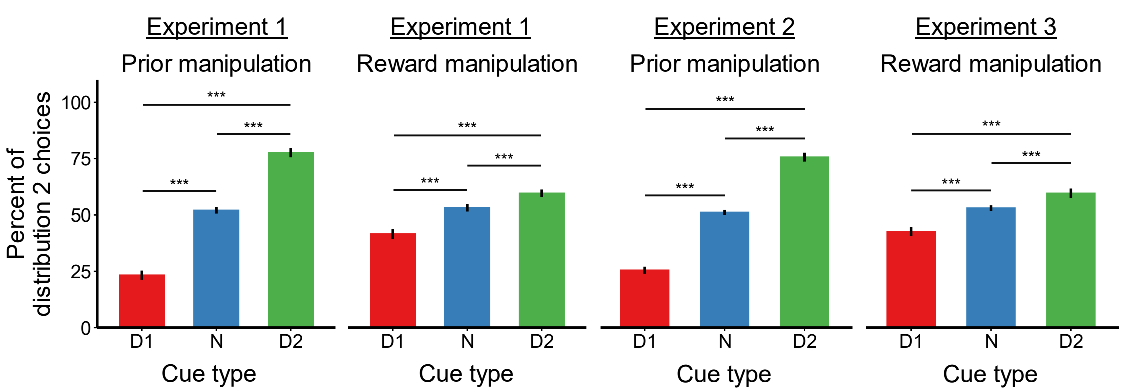


Figure 3. The effects of prior and reward cues on choice bias. As can be seen in the figure, participants' choices were significantly altered by cues both under the prior and reward manipulations, indicating that both manipulations were effective. D1, D2, and N represent cues that favor distribution 1, distribution 2 and neutral cues, respectively. Error bars depict *SEM*. ***, $p < .001$.

Of note, our results also demonstrate that the prior manipulation produced stronger biasing effects than the reward manipulation. This was true for Exp 1 where the difference in the proportion of distribution 2 choices for D2 vs. D1 cues were 54.3% vs. 18.1% ($t(20) = 10.24$; $p = 2.1\times10^{-9}$), as well as for Exp 2 vs. Exp 3 (difference between D2 and D1 choices = 50.2% and 17.1%, respectively; $t(61.76) = 6.92$; $p = 3.1\times10^{-9}$). This is despite the fact that the prior and reward cues had the same information value in Exp 1 (both would optimally induce a 3/1 bias), and that the reward cue had higher information value in Exp 3 than the prior cue had in Exp 2 (5/1 vs. 3/1, respectively). These results are in line of previous findings that human judgments are biased more by expectation compared to reward cues (Ackermann & Landy, 2015; Bohil & Maddox, 2001, 2003; Healy & Kubovy, 1981; Maddox, 2002; Maddox & Bohil, 1998; Maddox & Dodd, 2001).

3.2. DDM fits

We examined how the prior and reward cues affected DDM parameters. We fitted DDM separately to each participant's prior manipulation and reward manipulation data and examined whether the prior and reward cues induce a starting point change (assumed to index cognitive effects), a drift rate bias (assumed to index perceptual effects), or both. We found robust effects on the starting point z for both prior (Exp 1: $F(2,40) = 18.07$, $p = 2.6\times10^{-6}$; Exp 2: $F(2,62) = 79.43$, $p = 7.9\times10^{-18}$; Figure 4A,B) and reward manipulation (Exp 1: $F(2,40) = 26.54$, $p = 4.6\times10^{-8}$; Exp 3: $F(2,62) = 24.13$, $p = 1.8\times10^{-8}$; Figure 4A,C). Specifically, the starting point was shifted towards the boundary associated with that distribution both for p cues (D1 cues: -.41 in Exp 1 and -.65 in Exp 2; N cues: -.08 in Exp 1 and -.11 in Exp 2; D2 cues: .36 in Exp 1 and .64 in Exp 2) and reward cues (D1 cues: -.38 in Exp 1 and -.36 in Exp 3; N cues: -.08 in Exp 1 and -.06 in Exp 3; D2 cues: .24 in Exp 1 and .17 in Exp 3). These results are in line with the standard interpretation that cognitive effects should produce changes in the starting point in DDM fits.

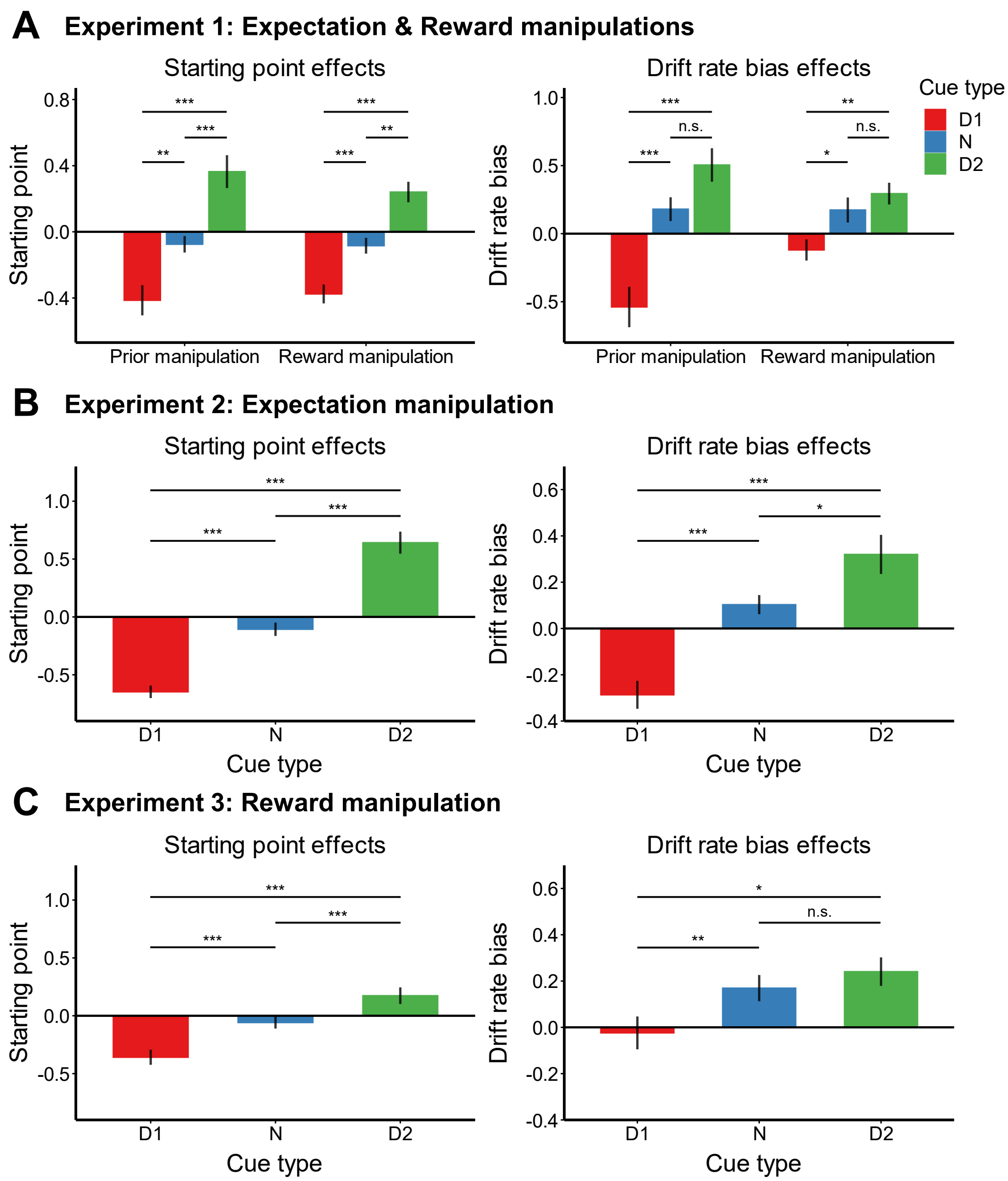


Figure 4. DDM parameters under prior and reward manipulations. (A) DDM parameters in Exp 1. Both prior and reward manipulations significantly altered both starting point and drift rate bias. (B) DDM parameters in Exp 2. The prior manipulation significantly altered both starting point and drift rate bias. (C) DDM parameters in Exp 3. The reward manipulation significantly altered both starting point and drift rate bias. D1, D2, and N represent cues that favor distribution 1, distribution 2 and neutral cues, respectively. Error bars show *SEM*. ***, $p < .001$; ** $p < .01$; * $p < .05$; n.s., not significant.

Critically, we examined whether the prior and reward manipulations led to drift rate biases that are proposed to index perceptual effects. We found robust effects on the drift rate bias for both prior (Exp 1: $F(2,40) = 16.23$, $p = 6.9\times10^{-6}$; Exp 2: $F(2,62) = 22.17$, $p = 5.5\times10^{-8}$; Figure 4A,B) and reward manipulation (Exp 1: $F(2,40) = 8.43$, $p = 8.9\times10^{-4}$; Exp 3: $F(2,62) = 6.85$, $p = .002$; Figure 4A,C). Similar to the starting point effects, the drift rate bias was shifted towards the boundary associated with that distribution both for prior cues (D1 cues: -.54 in Exp 1 and -.29 in Exp 2; N cues: .18 in Exp 1 and .10 in Exp 2; D2 cues: .50 in Exp 1 and .32 in Exp 2) and reward cues (D1 cues: -.12 in Exp 1 and -.02 in Exp 3; N cues: .17 in Exp 1 and .17 in Exp 3; D2 cues: .29 in Exp 1 and .24 in Exp 3). These results indicate that rather than simply mapping onto starting point changes, cognitive effects can also lead to drift rate bias changes. Thus, differences in drift rate bias cannot be automatically interpreted as indexing perceptual effects.

3.3. Peaks of the confidence and RT distribution

Having examined the first proposed signature of indexing perceptual effects via DDM parameter fits, we explored the second proposed signature according to which perceptual vs. cognitive effects are indexed by a change vs. lack of change in the peaks of the confidence and RT distributions. We first confirmed that in all three experiments, both the prior and reward manipulations significantly altered the cumulative normal distribution functions produced by plotting the probability of choosing distribution 2 as a function of the presented number. To test for this effect statistically, we computed the points of subjective equality (PSEs) – that is, the number for which participants choose distribution 2 exactly 50% of the time – for each type of cue separately. We found that the PSEs significantly differed between the different cues for both prior (Exp 1: $F(2,40) = 76.22$, $p = 2.3\times10^{-14}$; Exp 2: $F(2,62) = 59.73$, $p = 3.5\times10^{-15}$; Figure 5A,B) and reward manipulation (Exp 1: $F(2,40) = 16.44$, $p = 6.1\times10^{-6}$; Exp 3: $F(2,62) = 22.16$, $p = 5.5\times10^{-8}$). These results mirror the effects from Figure 3 and further support the notion that the manipulations were effective in biasing participants' choices.

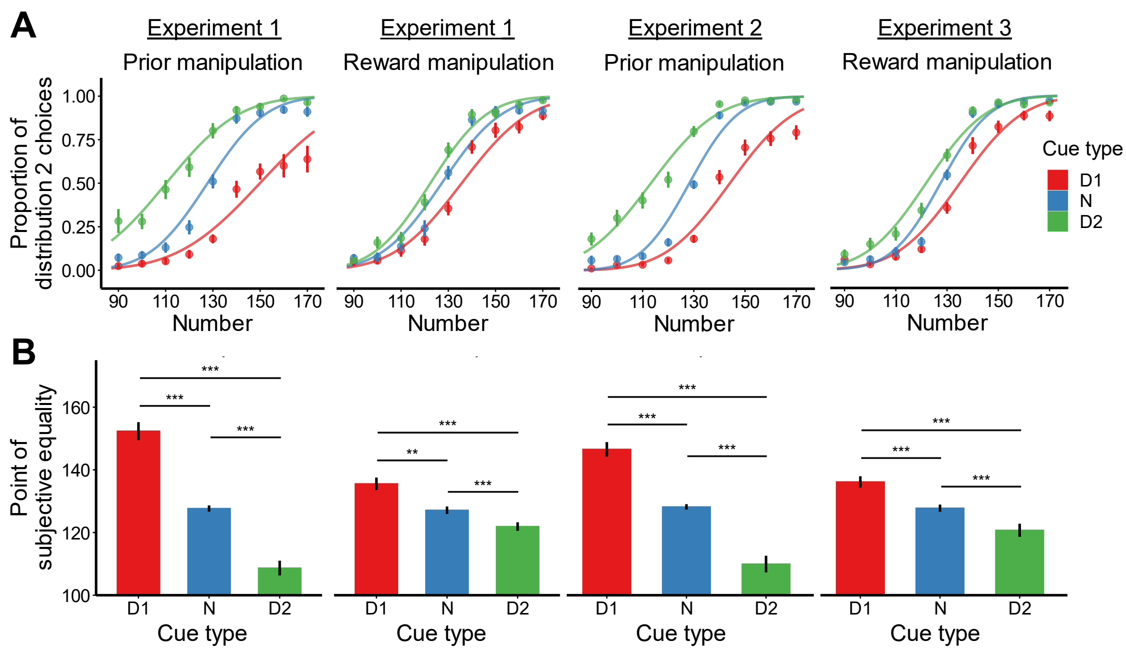


Figure 5. Psychometric curves under prior and reward manipulations. (A) Psychometric curves plotting the proportion of choosing distribution 2 as a function of the presented number under prior and reward manipulations. Both manipulations significantly altered the cumulative normal distribution function produced by plotting the probability of choosing distribution 2 as a function of the presented number. Circles with error bars represent empirical data plotted in bins of 10. Solid lines indicate best-fitting cumulative normal distribution functions fit to the raw data (without binning) aggregated across participants. (B) Point of subjective equality (PSE) under prior and reward manipulations. Bars were plotted by fitting psychometric curves to raw data from individual participants and then averaging PSEs over participants. Both manipulations significantly altered the PSEs, indicating the manipulations were effective. Error bars show *SEM*. ***, $p < .001$; ** $p < .01$.

Critically, we examined whether the peaks of the distributions for confidence ratings and RT remained stable (as predicted for purely cognitive effects) or were shifted by the cues (as predicted for purely perceptual effects). We found clear evidence for the distributions shifting under the prior manipulation (Figure 6). Indeed, the peak of the confidence distribution – that is, the point where confidence was the lowest – had lowest values for D2 cues (109.3 in Exp 1 and 111.5 in Exp 2), intermediate values for N cues (115.9 in Exp 1 and 119.8 in Exp 2), and highest values for D1 cues (144.0 in Exp 1 and 135.6 in Exp 2), with these differences being highly significant (Exp 1: $F(2,28) = 8.61$, $p = .001$; Exp 2: $F(2,56) = 23.80$, $p = 3.3\times10^{-8}$). We found similar effects for the reward manipulation with D2 cues generally producing the lowest peaks and D1 cues producing the highest peaks. However, consistent with the weaker biasing effects observed in that manipulation (Figure 3), we also observed smaller effects on the confidence distributions. The effects were significant in Exp 1 ($F(2,28) = 4.97$, $p = .014$) and in Exp 3 ($F(2,56) = 7.63$, $p = .001$). These results demonstrate that substantial shifts in the peaks of the confidence distributions can be observed with our purely cognitive task, especially for the prior manipulation.

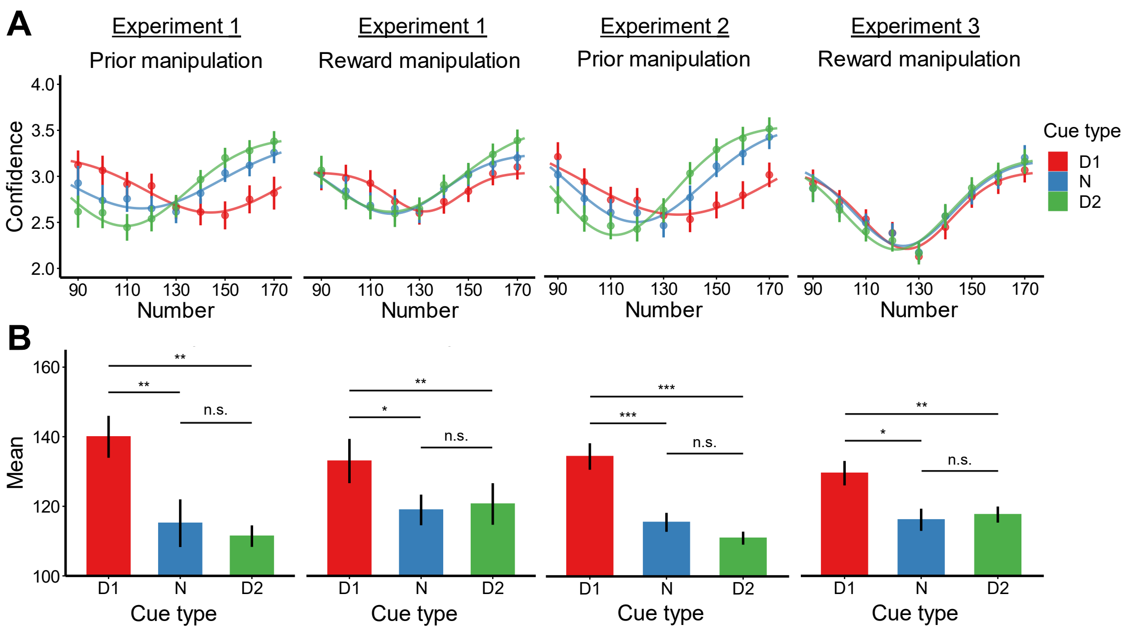


Figure 6. Confidence under prior and reward manipulations. (A) Distributions for confidence ratings under prior and reward manipulations produced by plotting confidence as a function of the presented number. Circles with error bars represent empirical data plotted in bins of 10. Solid lines indicate best-fitting raised Gaussian functions fit to the raw data (without binning) aggregated across participants. (B) Means of the raised Gaussian functions under prior and reward manipulations. Bars were plotted by fitting raised Gaussian functions to raw data from individual participants and then averaging means over participants. The means were significantly shifted under the prior manipulation, and were also shifted under the reward manipulation (significant in Exp 3, but not significant in Exp 1).

In addition to confidence, we also examined the equivalent effects for the RT distributions. Similar to the effects in confidence, we found that the distributions of RT were shifted under the prior manipulation with D2 cues generally producing peaks shifted to the right and D1 cues producing peaks shifted to the left (Figure 7). The effects fell just short of significance in Exp 1 ($F(2,38) = 1.79$, $p = .18$) but were significant in Exp 2 where we had more trials per subject ($F(2,54) = 22.74$, $p = 6.9\times10^{-8}$). However, the shifting effects were not significant under the reward manipulation in both Exp 1 ($F(2,38) = 1.22$, $p = .31$) and Exp 3 ($F(2,60) = 2.06$, p

= .14). The weaker effects on RT compared to confidence may be due to the fact that RTs tend to be noisier, which results in larger variability in the fits for individual participants. Nevertheless, given that the peak for the RT distribution for the D1 cues were numerically higher than the peak for the RT distribution for the D2 cues in all four analyses, it appears that the peaks of the RT distributions are problematic as a diagnostic tool for determining whether an effect is perceptual or cognitive.

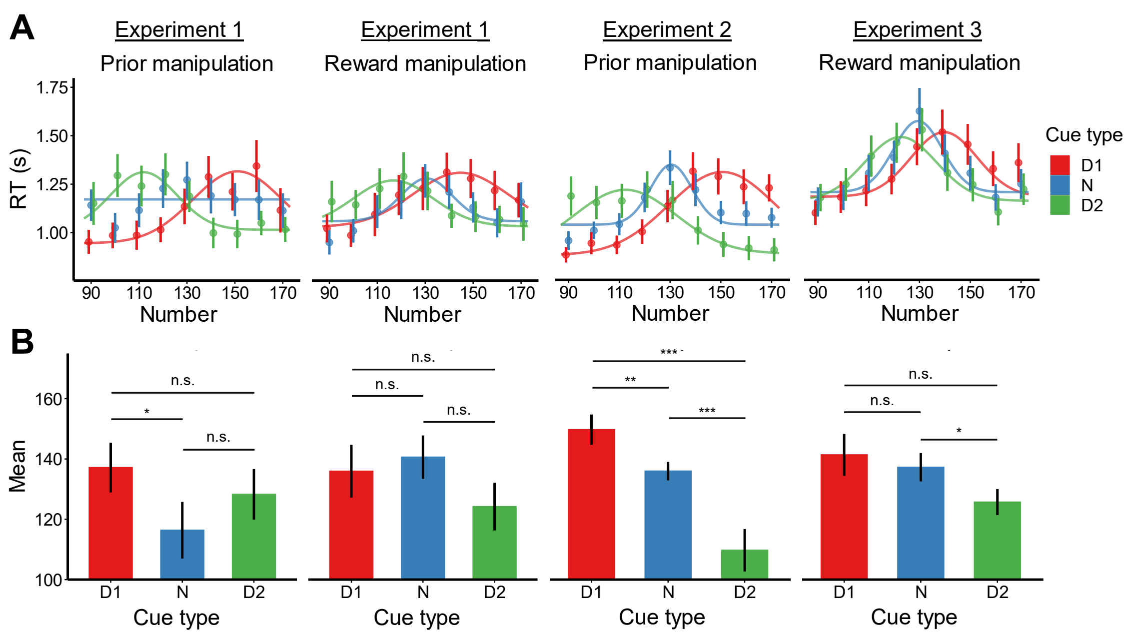


Figure 7. RT under prior and reward manipulations. (A) Distributions for RT under prior and reward manipulations produced by plotting RT as a function of the presented number. Circles with error bars represent empirical data plotted in bins of 10. Solid lines indicate best-fitting raised Gaussian functions fit to the raw data (without binning) aggregated across participants. (B) Means of the raised Gaussian functions under prior and reward manipulations. Bars were plotted by fitting raised Gaussian functions to raw data from individual participants and then averaging means over participants. The means were shifted under the prior manipulation (significant in Exp 2, but not significant in Exp 1), but the effect was not significant under the reward manipulation.

4. Discussion

We set to test two proposals about behavioral signatures that could potentially be used to distinguish between perceptual and cognitive effects. First, it has been proposed that different DDM parameters may map onto different effects, such that a drift rate bias indicates a perceptual effect, whereas a starting point shift indicates a cognitive effect. Second, another proposal states that, when plotted as a function of a sensory feature, changes in the peak of the distributions for confidence and RT may imply that a given manipulation's effects are perceptual rather than cognitive. Here we test both proposals in a purely cognitive task where all effects can only be cognitive. We find that both signatures previously associated with perceptual effects emerged naturally in the purely cognitive task. Our results demonstrate that individual DDM parameters or the peaks of confidence and RT distributions in isolation are insufficient to distinguish between perceptual and cognitive effects.

The first proposal holds that different DDM parameters map onto different effects. Specifically, a drift rate bias maps onto a perceptual effect, whereas a starting point shift maps onto a cognitive effect (Germar et al., 2014; Voss et al., 2008). Our results show that different cues in a purely cognitive task – manipulations that are cognitive in nature – could also change drift rate bias, thus challenging the one-to-one mapping between individual DDM parameters and the types of effects obtained. Our findings raise questions regarding the interpretation of the drift rate bias in DDM. Typically, drift rate is thought to mainly depend on the physical characteristics of external stimulus and the information uptake processes. Correspondingly, drift rate bias is considered to indicate perceptual biases and is unrelated to cognitive factors (Germar et al., 2014; Voss et al., 2008). In contrast, our results show that drift rate bias is indeed sensitive to cognitive manipulations (e.g., prior and reward manipulations in a purely cognitive task), which suggests that it can reflect richer cognitive processes rather than simply indexing perceptual processes.

Our work adds to Sánchez-Fuenzalida et al. (2022) in which the authors reported similar results in a perceptual discrimination paradigm where participants were required to discriminate lengths of a target and a reference line. Sánchez-Fuenzalida et al. found that different manipulations preferentially affected drift rate bias or starting point (e.g., the effect on drift rate bias were larger for perceptual than cognitive manipulations). However, different manipulations still did not uniquely change drift rate bias or starting point, supporting the notion that there is no one-to-one mapping between DDM parameters and different types of effects. Critically, given that DDM parameters may be quantitatively different for perceptual or cognitive effects, the parameters may still be diagnostic of different effects (e.g., one parameter moves more in one case than the other). That said, even if the DDM parameters are diagnostic, more work is needed to figure out how to draw conclusions about perceptual or cognitive effects based on DDM parameters in any given study.

The second proposal holds that while both perceptual and cognitive effects alter choices, only perceptual effects lead to shifts in the peaks of the confidence and RT distributions when they are plotted as a function of the sensory feature (Gallagher et al., 2019, 2021; Maldonado Moscoso et al., 2020). It is sensible to state that perceptual effects will certainly shift confidence and RT distributions since the raw sensory experience is changed under perceptual effects. However, cognitive effects are be largely heterogeneous. It is unclear whether different cognitive effects would show the same signatures. Previous proposals have examined specific types of cognitive effects, including effects caused by instructing participants to make default decisions (Gallagher et al., 2019), implied motion aftereffect (Gallagher et al., 2021), and reward manipulation (Maldonado Moscoso et al., 2020). In these cases, a decision shift is not accompanied by a shift in confidence or RT distributions. Our work challenges the proposals by showing that prior manipulation could shift the peaks of confidence and RT distributions in a purely cognitive task, and supports the notion that different cognitive effects could affect the signatures differently. Thus, observing a shift in confidence and RT distributions does not allow us to distinguish whether a manipulation leads to perceptual or cognitive effects, but if there is no such a shift, we can conclude with high degree of certainty that the effect is not perceptual.

Our findings raise the question of whether any other behavioral signatures can distinguish between perceptual and cognitive effects. Although our work suggests that certain kinds of behavioral measurements in discrimination tasks are insufficient to distinguish between perceptual and cognitive effects, it might be possible to go beyond simple discrimination paradigms. One way to distinguish different effects is through post-decisional cues coupled with reverse correlation analyses. Specifically, Bang and Rahnev (2017) argued that pre-stimulus cues can influence both sensory signal and decision processes, whereas post-stimulus cues can only influence decision processes. Thus, any putative perceptual effects of pre-stimulus cues can be uncovered by comparing their effects to those of post-stimulus cues. Bang and Rahnev showed that pre- and post-stimulus expectation cues had equivalent effects on how the stimulus information was used, which suggests that prior expectation induced by pre-stimulus cues produces cognitive rather than perceptual effects. A second way to distinguish different effects is through reproduction tasks. Sánchez-Fuenzalida et al. (2022) found that in a reproduction task where participants reproduced the line they had just seen, the reproduction error was uniquely affected by the Müller-Lyer illusion (likely inducing a perceptual effect), but not by prior or reward manipulations (likely inducing cognitive effects), suggesting that the reproduction tasks could direct reflect sensory experience without being confused by cognitive factors. While both methods can be used to distinguish different effects, they each have limitations in generalizability. The reproduction paradigm in Sánchez-Fuenzalida et al. (2022) can only apply to stimulus that can be easily reproduced, whereas the method in Bang and Rahnev (2017) only applies to information that could be presented either before or after the stimulus (e.g., it can’t be applied to the Müller-Lyer illusion). Thus, more methods are ideally needed to establish whether a manipulation leads to perceptual or cognitive effects.

Our approach of testing whether behavioral signatures appear in purely cognitive tasks can be used as a general method to determine whether a proposed signature can truly distinguish between perceptual and cognitive effects. This issue is critical in many debates in the field, such as the question of cognitive penetrability of perception where there continues to be an intense discussion on whether cognition influences raw experience or just decision-making (Firestone & Scholl, 2016). Studies often seek to find evidence that the raw sensory experience has been altered by a manipulation, but it is typically extremely challenging to demonstrate that any particular behavioral effect necessarily implies perceptual rather than cognitive effects. Our approach here of testing whether a behavioral signature appears in purely cognitive tasks provides a critical test for any proposal that seeks to establish that a manipulation has purely perceptual effects.

In conclusion, our work shows that neither drift rate bias effects nor changes in the peak of the distributions for confidence or RT can be interpreted as indexing perceptual effects. These results challenge previous proposals about diagnostic tools for perceptual effects and suggest the need for more careful interpretation of the underlying processes associated with behavioral measurements in perceptual decision-making tasks.

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