Decision and metacognitive computations carry evidence of unchosen options in multialternative decisions.

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Abstract

Humans often face decisions between multiple alternatives. However, our grasp of the computations underlying this process is still limited. While some evidence suggests that only the chosen alternative is represented at the decision stage, other findings indicate that information from unchosen alternatives remains accessible for decision computations. Furthermore, the amount and kind of information that reaches metacognitive levels remains unexplored. We ran two pre-registered experiments using a second-guess paradigm to understand to what extent humans retain information from choices that were discarded in a first guess. We found consistent above chance performance and metacognition in a second-guess with a 4 alternative (Exp. 1) and 12 alternative task (Exp. 2). Computational modeling suggests both the decision and metacognitive systems maintain a noisy version of the information from all alternatives. Overall, our results suggest that, although suboptimally, humans take into account evidence from unchosen options in multialternative perceptual decision making and metacognition.

Keywords: *perceptual decision making; metacognition; confidence; multialternative decisions; computational modeling.*

Statement of relevance

When deciding and metacognitively evaluating decisions involving multiple courses of action, it is unknown whether humans can encompass information from all available alternatives or merely retain data from the chosen option. In this work we ask participants to select the correct option among many alternatives. When their decision was incorrect we gave them a second opportunity. We found that participants had both above chance performance and metacognition on this second judgment. These results, coupled with computational models of the decision process, provide evidence that information of unchosen options is retained. However, the noise that corrupts this information is larger with 12 than with 4 alternatives. Our results point out that information of all alternatives competes in influencing a decision and informs confidence judgments for a meaningful metacognitive evaluation of the performance —although this information is not recovered in a completely optimal way.

Introduction

Perceptual decision making, i.e. decisions human observers make about sensory information (Hanks & Summerfield, 2017; Heekeren et al., 2008), have been extensively studied using 2-alternative forced choice (2-AFC) tasks. Empirically driven computational models of this process suggest that the observer takes into account the evidence supporting the two competing alternatives and the decision corresponds to the alternative with highest evidence (Shadlen & Kiani, 2013). However, as many decisions are not binary, there is a growing interest in understanding the nuances of multi-alternative decisions (Busemeyer et al., 2019; Churchland et al., 2008; Rahnev et al., 2022; Turner et al., 2018), that are thought to reflect more naturalistic scenarios than 2-AFC paradigms (Yeon & Rahnev, 2020).

A key question in multi-alternative decision making is whether humans hold individual representations of all available alternatives to arrive at a decision —an assumption of virtually all computational models of decision-making— or, alternatively, humans create an abbreviated representation of all options, encoding only the most subjectively salient or valuable stimuli. Recently, Yeon & Rahnev (2020) designed an experimental framework involving "second guesses" in which participants were allowed to revise their choice after an initial incorrect decision. If information from the remaining alternatives is lost at the second guess stage, performance would be expected to reach chance levels. Conversely, if information from unchosen alternatives can reach the decision stage and it is effectively used to make a second judgment, then above-chance performance levels should be found. Their findings favored a "Summary" model in which solely the information from the chosen alternative contributes to the decision representation, suggesting that a great loss of information occurs in multi-alternative perceptual decision making. In contrast, McLean et al. (2020) found that participants' second-guesses performance was significantly above-chance, suggesting that decision computations have access to the evidence from unselected alternatives —a result inline with previous multi-alternative studies (Busemeyer et al., 2019; Churchland et al., 2008; Dumbalska et al., 2020; Niwa & Ditterich, 2008a; Turner et al., 2018).

In addition, the impact of these two scenarios on metacognition —the ability to monitor our own cognitive processes (Fleming, 2024)— remains untested. On one hand, the summary encoding view implies that the metacognitive system has no information to evaluate the quality of a second judgment. On the other hand, if unchosen options evidence can reach decision stages, then there is the possibility of meaningful metacognitive evaluation of those decisions. Moreover, previous models suggest a separate route of evidence for metacognitive computations (Maniscalco & Lau, 2016), which could lead to dissociations between decision performance and metacognition in multi-alternative judgments.

To arbitrate between this contradictory evidence and clarify the nature of the multi-alternative decision and metacognitive representations, we carried out two pre-registered experiments that varied in the amount of alternatives and put to test three computational models with different degrees of loss of information. Participants had to identify the largest geometrical figure from a set and were given a second opportunity to make a choice if their initial selection was incorrect. In addition, they were requested to report their confidence in this second judgment, which allowed us to test whether a dissociation between decision and metacognitive levels regarding the amount and type of evidence used for computations was present (Fleming & Dolan, 2012).

To summarize, our results indicate that information from all alternatives is present at the decision and metacognitive stages. This was reflected in above chance levels for both second guess performance and metacognitive sensitivity in both a 4-alternative context (Experiment 1) as well as in a 12-alternative context (Experiment 2). Nevertheless, our results do not support the view that an exact copy of the sensory information is available at those levels, since the best fitting model included extra noise at the second-guess stage. Importantly, more alternatives induced a higher amount of information loss, as illustrated by the results found in Experiment 2 where smaller effect sizes were found and where the model that proposes that an exact copy of the sensory information is present at decision and metacognitive levels —which was as good as the model with the extra noise parameter in Experiment 1— was the worse-fitting model.

Methods – Experiment 1

Experiment 1 was programmed in JavaScript using the library jQuery and ran on a JATOS (Lange et al., 2015) server. The experimental protocol was approved by the ethical committee of the Psychological Research Institute (National University of Córdoba & National Scientific and Technical Research Council – Córdoba, Argentina). The experiment was pre-registered https://osf.io/9w6ju.

Participants

18 participants took part in Experiment 1 (13 females; M_{age} = 24.5; SD_{age} = 3.37). Sample size was calculated using the GPower software to reach >80% power to detect a significant difference in the t-tests performed (see the pre-registration at https://osf.io/9w6ju for details). Participants read and accepted an informed consent sheet prior to the experiment. All participants reported no psychiatric or neurological history and no chronic consumption of psychoactive substances.

Procedure and experiment design

Experiment 1 (Figure 1A) involved a 4-alternative perceptual decision making task. Participants sat 81 centimeters away from the screen, and completed two experimental sessions on different days, each including 10 practice trials and 350 experimental trials. First, participants were presented with a fixation dot displayed on the center of the screen for 800ms, followed by a stimuli array consisting of geometrical shapes (squares and circles) in a 2x2 grid for 500 ms (stimuli were separated both vertically and horizontally by 6.31° of visual angle). The task was to identify the largest shape among randomly presented squares and circles. Only a single figure was the largest, and the others were equally sized. The largest figure had an equal probability of appearing in any position. The largest figure had a mean size of 1.33° of visual angle, with a standard deviation of 0.33° of visual angle. To pick a figure, participants clicked on the position where the figure they believed was the largest one was present (positions were signaled with small dots after stimuli disappearance). If the decision was correct, the next trial began automatically. Otherwise, they had a second opportunity to choose one of the remaining figures. Chance level for this second decision is therefore defined as a proportion of correct trials of $\frac{1}{3}$, since it is made on 3 alternatives. After each second judgment, participants reported their confidence on being correct on a 4-point scale by clicking on any of four buttons representing the scale. The spanish phrases “nada seguro” and “completamente seguro” (translating to “not sure at all” and “completely sure”, respectively) were displayed below the 1 and 4 buttons, respectively. A 1up/1down staircase was implemented on the first 60 trials of the task to obtain 50% accuracy on the first choice, to ensure a sufficient number of second decisions. The variable controlled by the staircase was the size of the incorrect alternatives, defined as a proportion of the area of the correct alternative. After each incorrect choice the size of the incorrect alternatives decreased by a proportion of the area of the correct alternative equals to .005, whereas after each correct choice this proportion increased by .005. After the first 60 trials, the average size difference from trials 50 to 60 was computed and this was the size difference between correct and incorrect figures used in the rest of the trials. In each session, two rest pauses were included at trials 120 and 240. In those breaks, a message informing participants that they can take a couple of minutes to rest was presented on the screen. Participants clicked anywhere on the screen to continue with the experiment after the rest period.

Data analysis

We excluded trials with response times (RT) larger than 8 s or shorter than 150 ms on any of the responses (first and second decision, and confidence report). We discarded the first 60 trials (which included the practice trials and the trials with the staircase). No subject was excluded. Our predefined alpha level was .05.

For each subject, we computed the proportion of correct responses on the first decision (first decision performance), the proportion of correct responses on the second decision (second decision performance) and metacognitive sensitivity on the second decision. We operationalized metacognitive sensitivity as the area under a Receiver Operating Characteristic curve (Fleming & Lau, 2014).

We used one-tailed t-tests to compare the second decision performance and the metacognitive sensitivity level to chance levels ($\frac{1}{3}$ and $\frac{1}{2}$, respectively). We also explored, using linear regression models, if second decision performance was predicted by first decision performance and if metacognitive sensitivity was predicted by second decision performance.

All of these analyses and criteria were pre-registered and can be found at https://osf.io/9w6ju.

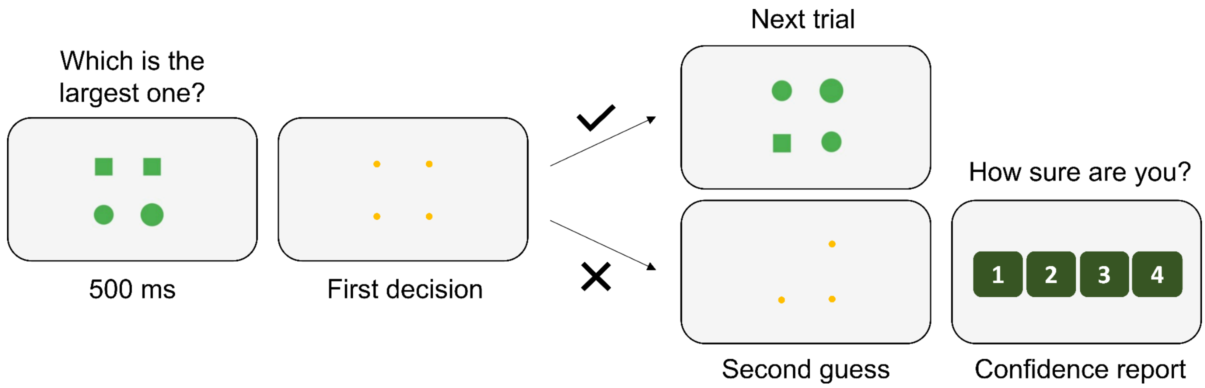

Figure 1 – Experiment 1 task. Experiment 1 consisted of a size discrimination task where participants had to identify the largest geometrical shape within a set. If a decision was correct, the next trial began automatically. Otherwise, participants had a new chance to identify the figure out of the remaining ones. After this second guess, participants reported their confidence on being correct on a 4-point scale.

Computational modeling

We compared three different computational models to evaluate different possible information processing scenarios regarding the evidence available in multi-alternative perceptual decision making. Each model points to a different degree of loss of information. All models start with the same process: random samples (one for each alternative) are generated from a Gaussian distribution with mean μ_i (fixed at 1 for the largest alternative and to the proportion of the area of the largest figure obtained for each subject for the rest of the alternatives) and standard deviation σ. While μ_i are fixed, σ is fitted to each participant by maximizing its log-likelihood given the data (first decisions, second decisions and metacognitive sensitivity). The first decision corresponds to the geometrical figure associated with the highest sample obtained. If the decision is correct, the trial ends. If the decision is incorrect, three possibilities arise, each corresponding to a different model. We next describe each model in detail.

Summary model. The Summary model proposes that the observer arrives at a decision taking into account only the information of the alternative with the highest obtained sample, following the proposal of Yeon and Rahnev (2020). Hence, when prompted for a second decision, the observer has no information about non-chosen alternatives, leading to both a random decision and random confidence levels.

Population model. The Population model proposes that at the decision instance the activity of all the alternatives is represented and sustained until the end of the decision process (McLean et al., 2020; Yeon & Rahnev, 2020). Therefore, when prompted for a second decision, the observer will choose the alternative whose associated evidence is maximum out of all previously non selected options (i.e., the second highest sample overall). Confidence on this second decision under this model can have several mappings: it can reflect the level of activation of the alternative chosen ("*Max model*"; Zylberberg et al., 2012), the difference between the two highest activations ("*Balance of evidence model*"; Li & Ma, 2020; Mamassian, 2016), the sum of the differences between the highest activation and the rest ("*Contrast* *model*"; Comay et al., 2023), and the difference between the activation of chosen alternative and the mean of the rest activations ("*Average-residual model*"; Comay et al., 2023).

Population + noise model. The Population + noise model proposes that, as in the Population model, at the decision instance the activity of all the alternatives is represented. However, random Gaussian noise with mean 0 and standard deviation σ_2 corrupts the samples at the second decision stage. σ_2 is a free parameter fitted to each subject by maximizing its log-likelihood. Confidence has the same possible mappings as in the Population model.

In order to compute metacognitive sensitivity, in all models a confidence criterion β parameter is fitted to each subject by maximizing its log-likelihood. This parameter categorizes models' predicted confidence into high and low, and this transformed confidence is used to compute the AUROC-2 predicted by the model.

Model fitting procedure

We fitted the free parameters (σ, β and σ_2 in the case of the Population + noise model) by maximizing their log-likelihood. To compute the log-likelihood we simulated 2000 trials and computed the model's probability of being correct on the first and second decisions and the predicted metacognitive sensitivity. We repeated this process 10 times, and took the mean of the 10 probabilities of being correct on the first and second decisions to approximate the true probabilities predicted by the model. We computed the probability of the data given the parameters values using the binomial data model and the previously calculated probabilities using the *dbinom* function in R. To model metacognitive sensitivity we followed a similar approach but using a normal data model: using the *dnorm* function in R we computed the probability of the metacognitive sensitivity data given the parameters. To calculate the mean and standard deviation of the normal distribution we computed the mean metacognitive sensitivity of the 10 simulations and the standard deviation of those simulated metacognitive sensitivities, respectively.

We started the fitting procedure with a coarse grid search to find sensible initial values for the parameters and then runned 3 gradient descent routines using the *optim* function in R. In order to have different initial values, for each routine we slightly corrupted the initial values of the parameters with Gaussian noise with mean zero and 0.05 standard deviation.

For the Population and the Population + noise model we fitted four different variations of the model, each differing in the confidence mappings. The best fitting variation (i.e., the one with maximum log-likelihood) was selected for comparison between models.

Parameter recovery

We ran a parameter recovery analysis and found that our method was able to recover the true parameters values. We obtained significant Pearson correlations between the true and the recovered parameters of 0.80 ($p < .001$, *CI* = [0.71; 0.86], *df* = 98) for the σ parameter, to 0.36 ($p < .001$, *CI* = [0.17; 0.52], *df* = 98) for the σ_2 parameter and to 0.32 ($p = .001$, *CI* = [0.14; 0.49], *df* = 98) for the β parameter.

Model comparison

We compared the performance of the three models by using the Bayesian Information Criterion (BIC). We ran Welch's two sample t-tests between the models using the BIC values of each subject under each model. The formula used for the BIC was:

$$BIC_i = k\,log(n) - 2\,log(L_i)$$

Where k is the number of free parameters (2 for the Summary and Population model, 3 for the Population + noise model), n is the number of data points (600), L is the likelihood of the parameters given the data and i indexes the subjects.

Results – Experiment 1

Behavioral results

Participants had a mean performance for the first decision of 0.68 (*SD* = 0.06; Figure 2A). Importantly and as predicted in the pre-registration, participants showed above chance second decision performance (t_{17} = 10.03, p < .001, d = 2.36, M = 0.54, CI = [0.51; Inf]; Figure 2B) and also above chance metacognitive sensitivity (t_{17} = 8.92, p < .001, d = 2.10, M = 0.61, CI = [0.59; Inf]; Figure 2C).

We next explored how these variables related to each other. We found that first decision performance significantly predicted performance in the second decision ($F_{1,16}$ = 14.5, $\beta_{first\ decision}$ = 0.95, SE = 0.25, p = .002, R^2 = 0.44; Figure 2D) and second decision performance significantly predicted metacognitive sensitivity ($F_{1,16}$ = 9.48, $\beta_{second\ guess}$ = 0.36, SE = 0.12, p = .007, R^2 = 0.33; Figure 2E).

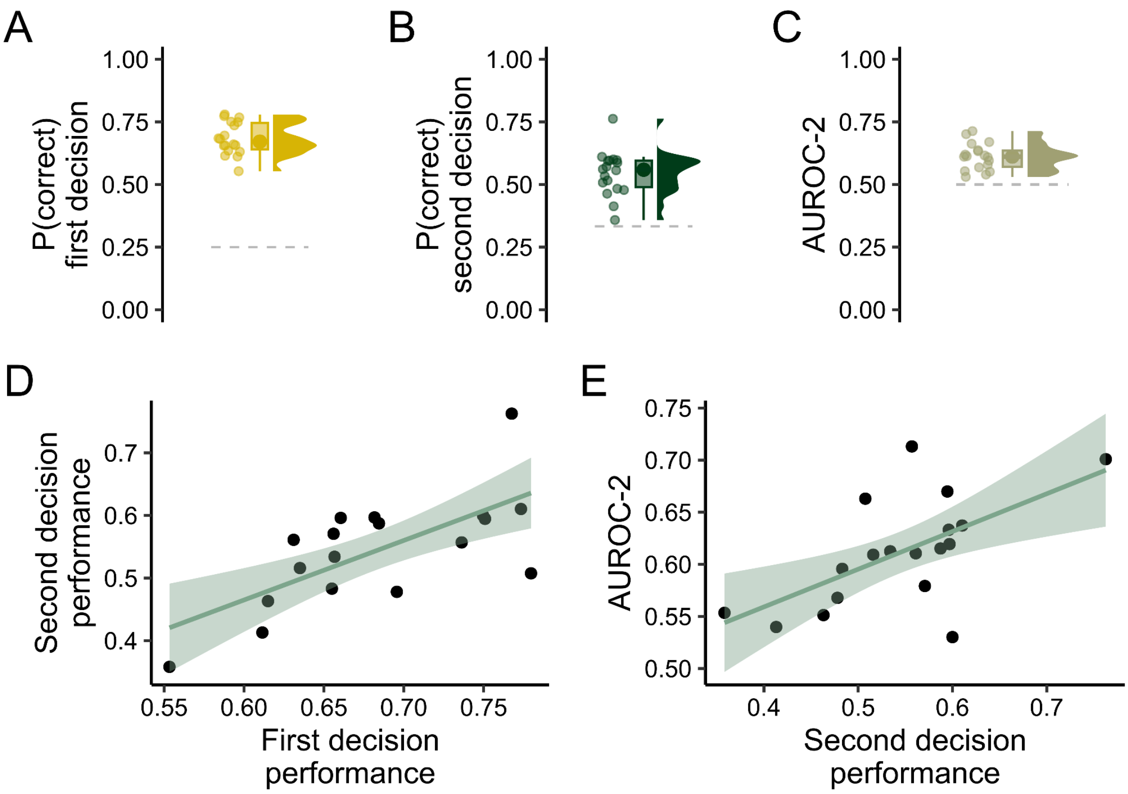

Figure 2 – Experiment 1 behavioral results. A) Performance on the first decision. B) Second decision performance was significatively above chance level. C) Metacognitive sensitivity was significantly above chance level. In panels A, B and C chance level is depicted by the gray horizontal dotted lines, jittered dots represent the score of an individual participant, box plots depict the median and the interquartile range (with whiskers that represent 1.5 IQR) and the curves represent the density of the data. D) An increase in first decision performance significantly predicted an increase in second decision performance. E) An increase in the second guess performance predicted an increase in metacognitive sensitivity. In panels D and E dots represent individual participants, solid lines represent the regression line and the smoothed area represents the 95% confidence interval.

Computational modeling

As predicted, the Summary model could not fit the pattern found in our data. Indeed, despite accurately predicting first decision performance, the model underestimated second decision performance and metacognition, thus strongly deviating from empirical data (Figure 3 – top row). On the other hand, the Population model and the Population + noise model were better at accommodating the pattern of our data (Figure 3 – middle and bottom rows). The Population model, however, overestimated the accuracy of the second judgment made by the participants. By comparing the models using the BIC to correct for the number of parameters, we found that both the Population and the Population + noise models were better than the Summary model (Population + noise model vs Summary model: $t_{17.57}$ = –5.72, p < .001, d = 1.91, $M_{PopNoise}$ = 27.44, $M_{Summary}$ = 70.83, CI = [–59.34; –27.43]; Population model vs Summary model: $t_{19.35}$ = –5.85, p < .001, d = 1.95, $M_{Population}$ = 25.31, $M_{Summary}$ = 70.83, CI = [–61.77; –29.26]; Figure 7A), but there was not a significant difference regarding BIC scores between the Population and the Population + noise models ($t_{24.76}$ = –0.97, p = .344, d = 0.32, $M_{Population}$ = 25.31, $M_{PopNoise}$ = 27.44, CI = [–6.68; 2.42]; Figure 7A).

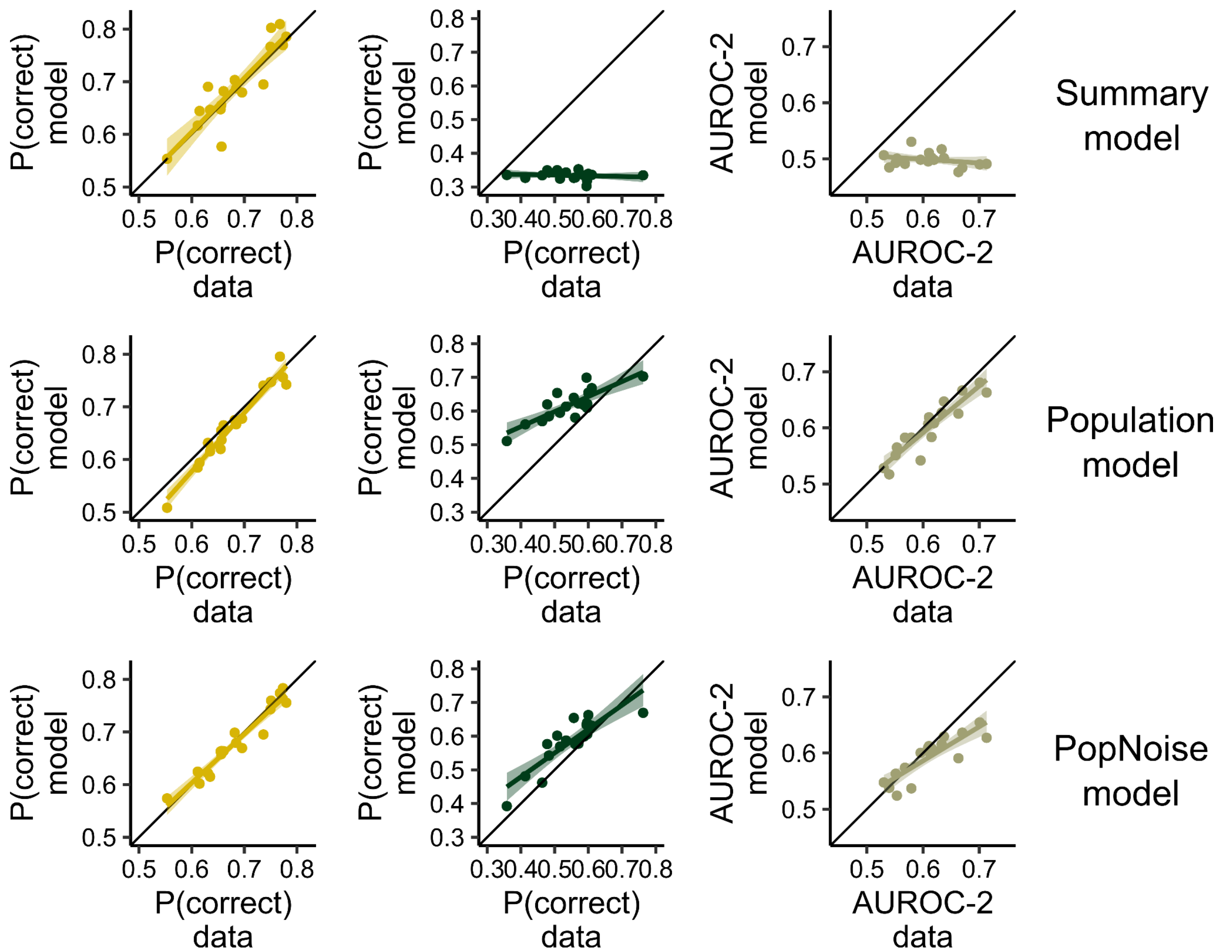

Figure 3 – Experiment 1 model fitting results. While accurately predicting the performance on the first judgment, the Summary model underestimated both second decision and metacognitive performance (*top row).* In contrast, both the Population model (*middle row*) and the Population+noise model (*bottom row*) accurately fitted the data with the Population model overestimating the second decision performance. In all panels dots represent individuals, solid lines represent regression lines and shaded regions represent 95% confidence intervals. Yellow panels (*first column*) represent first decision data, dark green panels (*second column*) represent second decision data and olive panels (*third column*) represent metacognitive data.

Methods – Experiment 2

Results of Experiment 1 point out that information from all four alternatives is not entirely lost and informs the decision-making and metacognitive processes. As pre-registered, we subsequently expanded our investigation by testing with 12 alternatives.

As in Experiment 1, Experiment 2 was programmed in JavaScript using the library jQuery and ran on a JATOS (Lange et al., 2015) server. The experimental protocol was approved by the ethical committee of the Psychological Research Institute (National University of Córdoba & National Scientific and Technical Research Council – Córdoba, Argentina). The experiment was pre-registered https://osf.io/d5qyp/.

Participants

18 participants took part in Experiment 2 (14 females; M_{age} = 23.78; SD_{age} = 2.94). Sample size was calculated using the GPower software to reach >80% power to detect a significant difference in the t-tests performed (see the pre-registration at https://osf.io/9w6ju for details) Participants read and accepted an informed consent sheet prior to the experiment. All participants reported no psychiatric or neurological history and no chronic consumption of psychoactive substances.

Procedure and experiment design

Experiment 2 (Figure 4) was identical to Experiment 1 but with twelve instead of four alternatives. The procedure was exactly the same as in Experiment 1: participants sat 81cm from the screen and completed two sessions of 360 trials each in two different days. Figures were displayed on a 3x4 grid, and were separated (vertically and horizontally) by the same degrees of visual angle as in Experiment 1. As a result, the farthest from the center that an alternative could be was 9.46° horizontally and 6.31° vertically. Chance level for the second guess performance was equal to $\frac{1}{11}$, since 11 alternatives are left for the second judgment.

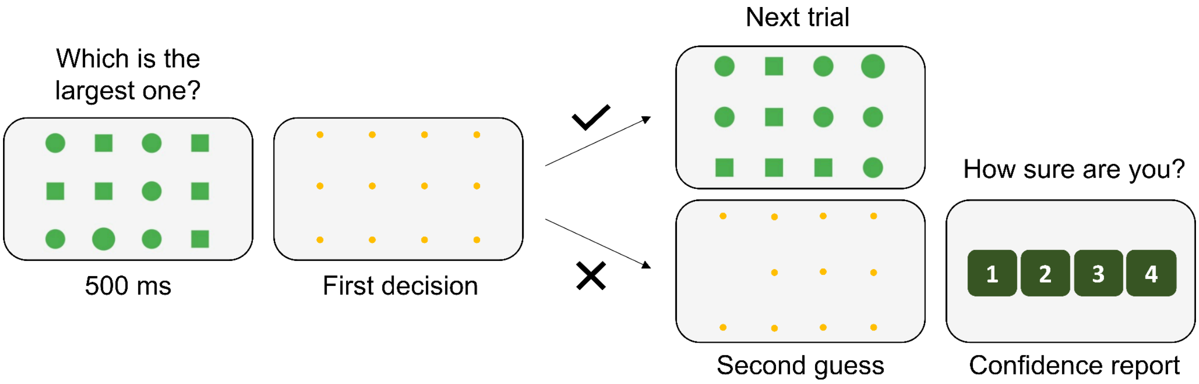

Figure 4 – Experiment 2 task. The task was identical to Experiment 1, but comprising twelve instead of four alternatives.

Data analysis

We followed a procedure similar than for Experiment 1, with the difference that the chance level used for the t-test on the second guess performance was equal to $\frac{1}{11}$. All of these analyses and exclusion criteria were pre-registered: https://osf.io/9w6ju.

Results – Experiment 2

Behavioral results

In spite of the much larger number of alternatives, similar results were obtained in Experiment 2. Performance on the first decision had a mean of 0.60 (SD = 0.06; Figure 5A). Participants again showed above chance second guess performance (t_{17} = 9.40, p < .001, d = 2.22, M = 0.20, CI = [0.18; Inf]; Figure 5B) and also above chance metacognitive sensitivity (t_{17} = 6.89, p < .001, d = 1.62, M = 0.59, CI = [0.57; Inf]; Figure 5C). Note that, as predicted, effect sizes were smaller on this experiment.

When exploring the relationships between these variables, we found that —contrary to the Experiment 1 results— performance on the first decision did not predict second decision performance ($F_{1,16}$ = 2.62, $\beta_{first\ decision}$ = 0.28, SE = 0.17, p = 0.12, R^2 = 0.09; Figure 5D) and performance on the second decision did not predict metacognitive sensitivity ($F_{1,16}$ = 0.01, $\beta_{second\ guess}$ = –0.03, SE = 0.28, p = .92, R^2 = –0.06; Figure 5E).

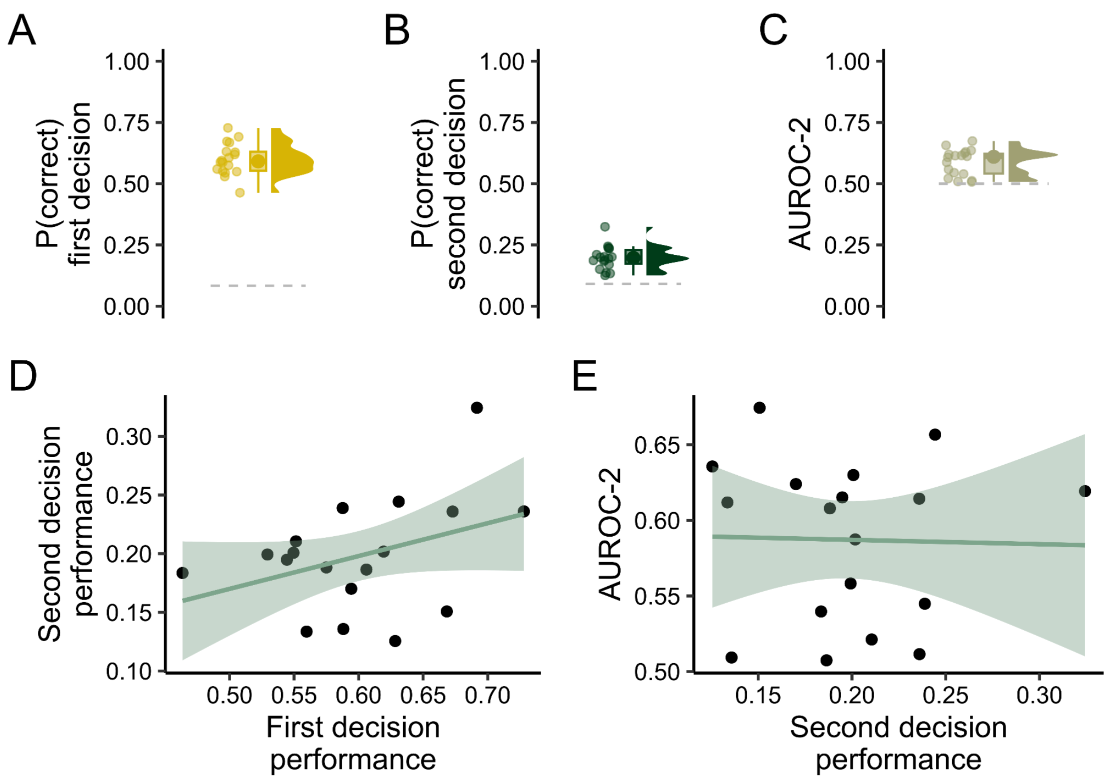

Figure 5 – Experiment 2 behavioral results. A) Performance on the first decision. B) Second decision performance was significatively above chance level. C) Metacognitive sensitivity was significantly above chance level. E and D) Contrary to Experiment 1, an increase in first decision performance did not predict an increase in second decision performance and an increase in the second guess performance did not predict an increase in metacognitive sensitivity. The conventions on this figure are the same as in Figure 2.

Computational modeling

We again found evidence against the Summary model, as this model underestimated participants' ability to perform meaningful second judgments and to give accurate confidence ratings that led to above-chance metacognitive sensitivity (Figure 6 – top row). However, and in line with the prediction that more information will be lost in this second experiment, the worst-fitting model was the Population model, which overestimated second decision performance and underestimated first decision performance (Figure 6 – middle row). The best-fitting model was the Population + noise model. Interestingly, despite a better fitting, the model underestimated participants' metacognitive sensitivity (Figure 6 – bottom row).

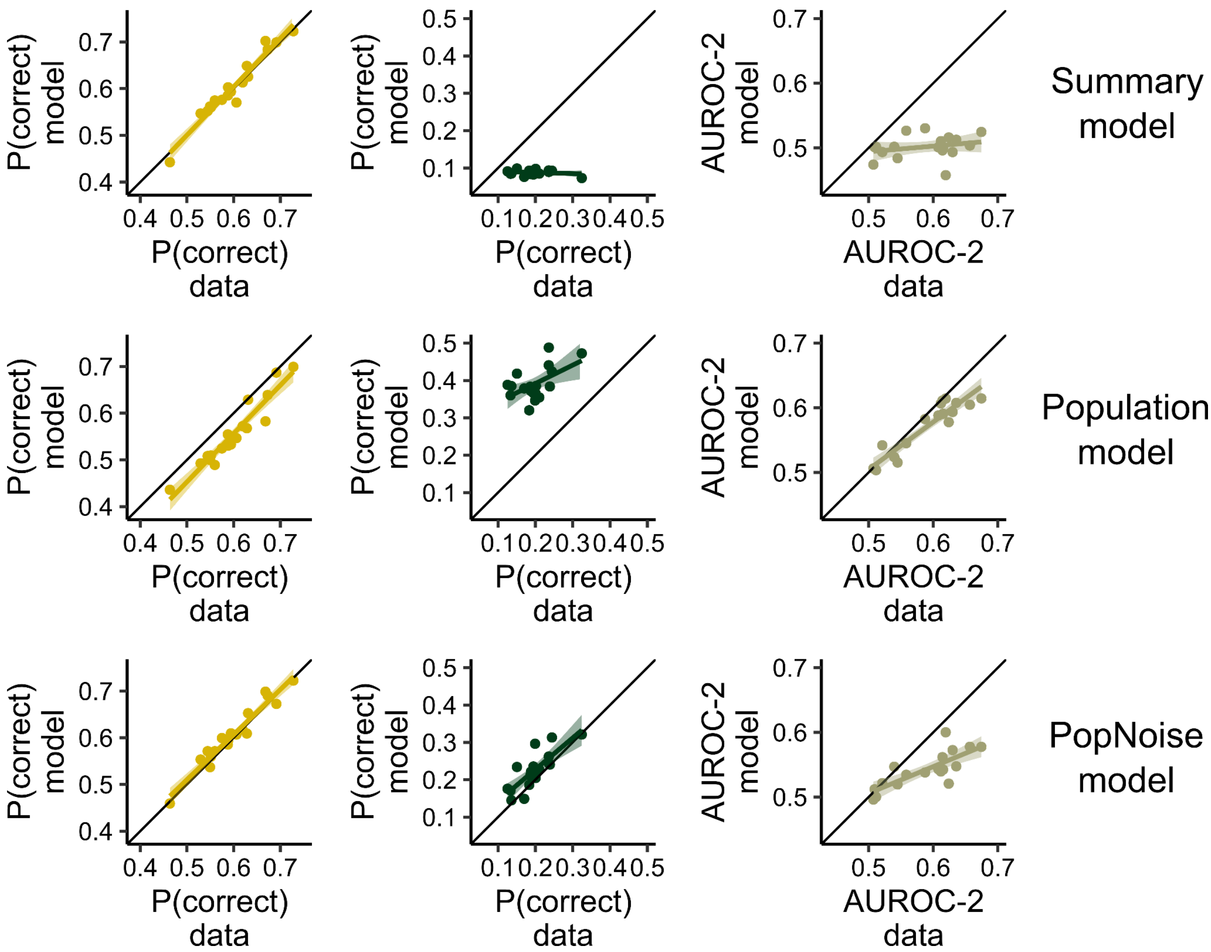

Figure 6 – Model fitting results on Experiment 2. Similar to the results on Experiment 1, the Summary model underestimated both second decision and metacognitive performance (*top row).* The Population model consistently underestimated first decision performance and overestimated second decision performance (*middle row*). The Population + noise (*bottom row*) was the best-fitting model, accurately predicting first and decision performance but underestimating metacognitive sensitivity. The conventions in this figure are the same as in Figure 3.

We compared the BIC of the models between them and found that the Population + noise model was significantly better than the Summary model ($t_{21.17}$ = –4.44, p < .001, d = 1.48, $M_{PopNoise}$ = 30.34, $M_{Summary}$ = 50.61, CI = [–29.77; –10.78]; Figure 7B) and the Population model ($t_{20.36}$ = –6.55, p < .001, d = 2.19, $M_{PopNoise}$ = 30.34, $M_{Population}$ = 63.44, CI = [–43.62; –22.59]; Figure 7B). Interestingly, we found marginally significant evidence that the Summary model fitted the data from Experiment 2 better than the Population model ($t_{33.59}$ = 1.98, p = .055, d = 0.66, $M_{Population}$ = 63.44, $M_{Summary}$ = 50.61, CI = [–0.30; 25.96]) (Figure 7B).

Taking into account both experiments, we found that the Population + noise model was the overall best fitting model, being significantly better than both the Population ($t_{38.51}$ = –3.67, p < .001, d = 0.86, $M_{PopNoise}$ = 28.89, $M_{Population}$ = 44.38, CI = [–24.03; –6.94]) and the Summary ($t_{37.82}$ = –6.78, p < .001, d = 1.60, $M_{PopNoise}$ = 28.89, $M_{Summary}$ = 60.72, CI = [–41.33; –22.33]) models (Figure 7C). The Population model was the second best fitting model, as it was better than the Summary model ($t_{69.16}$ = 2.65, p = .01, d = 0.62, $M_{Population}$ = 44.38, $M_{Summary}$ = 60.72, CI = [4.03; 28.66]; Figure 7C).

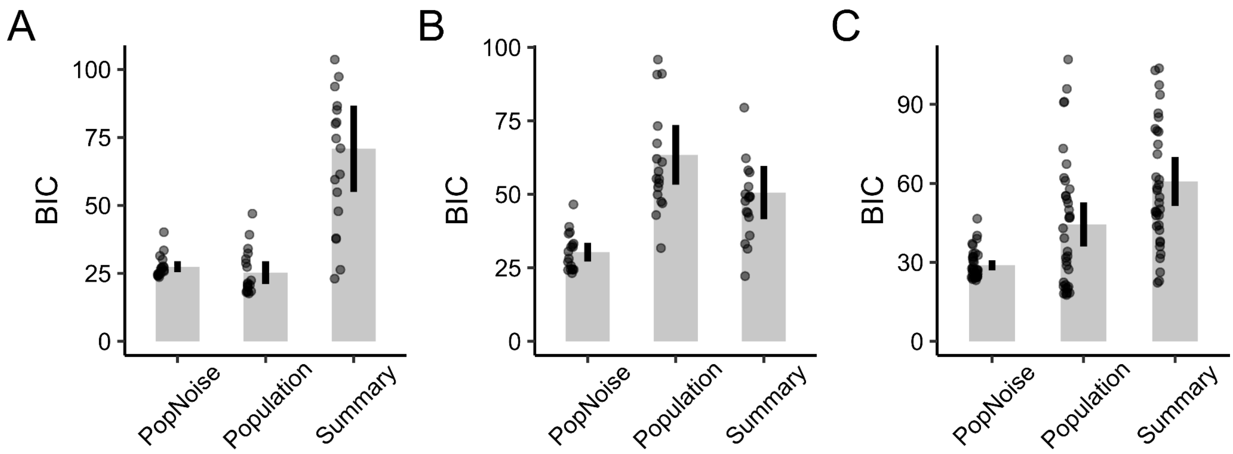

Figure 7 – Model comparison through the Bayesian Information Criterion. (A) The Population and the Population + noise models were the best fitting models on Experiment 1. (B) On Experiment 2, the Population + noise model was the best fitting model, while the Population model was the worst. (C) By combining the results of the two Experiments we found compelling evidence that the Population + noise model was the best fitting model to our data. Dots represent individual scores, columns represent mean values and vertical bars represent 95% confidence intervals. Note that higher scores of BIC means worse fitting.

Discussion

In the present work we have studied the multialternative representations of decision-making and metacognition. The underlying motivations were that contradictory results were found regarding the amount of information available at the decision stage (McLean et al., 2020; Yeon & Rahnev, 2020) and, moreover, there was an open question about whether this —or different— information can reach the metacognitive level.

Our results suggest that human decision-makers can recover information from unchosen alternatives in order to give meaningful second guesses and confidence ratings, even in complex multialternative contexts. Nevertheless, the idea of decisions and metacognitive representations carrying on an exact copy of the sensory information is not supported by the data, as the Population model was outperformed by the Population + noise model. This latter model includes extra noise that corrupts the decision representation at the second decision stage, meaning that some —but not all— information gets lost at this level, thus conciliating previously contradictory results. Indeed, as Yeon and Rahnev (2020) suggest, an exact copy of the sensory information may be present in more automated processes —such as multisensory integration— or in simple 2AFC tasks, but for multialternative decisions, the decision making and metacognitive systems appear to lose some of the available information.

Traditionally, perceptual decision making and metacognition have been studied using 2AFC tasks. The computational models developed under this approach assume that the information from the competing alternatives is represented by the observer, and the decision is made by judging the relative evidence for each alternative (Shadlen & Kiani, 2013). Our results suggest that this assumption extends to multialternative decisions, as even in a 12-alternative decision making task human observers can recover information from unchosen options. Moreover, metacognitive computations can access this information too as metacognitive sensitivity was above chance in both experiments.

The fact that —although noisy— information from unchosen alternatives accesses the decision stage is also inline with several contextual effects that arise in multi-alternative decision making tasks both in decisions (Busemeyer et al., 2019; Trueblood et al., 2013) and in confidence judgments (Comay et al., 2023). Moreover, as most computational accounts of these effects rely on the assumption that information of all alternatives is available and combined in a specific —non rational— way (Busemeyer et al., 2019; Dumbalska et al., 2020; Turner et al., 2018), the evidence reported here is then critical to sustain those explanations.

How can our results and those obtained by McLean et al (2020) be reconciled with those reported in Yeon & Rahnev (2020) —pointing to a strong loss of sensory representation during decision stages? One possibility is that other factors apart from the amount of alternatives influence the loss of information in multi-alternative perceptual decision making. Rosenholtz (2020) indicates that two main factors influence the loss of information in visual perception: the limits that peripheral vision gives for performing certain tasks and the limits of the decision mechanisms that cannot perform arbitrarily complex tasks. In this sense, Yeon & Rahnev (2020) tasks induce loss of information according to these two main factors. First, the information of the stimuli used in their Experiments 1, 2 and 3 —symbols and colors much more complex than stimuli in our tasks— may be lost already in the peripheral encoding as, for instance, color peripheral vision is limited and the distinction of features that requires binding (such as distinguishing between letters or symbols) requires selective attention and are propense to crowding effects (Rosenholtz, 2016, 2020). Second, these tasks involve both recognizing each individual stimulus and estimating their frequency while taking into account the frequency of the other stimulus categories (a kind of triple task that can also induce loss of information due to decision complexity, see Rosenholtz, 2020). On the other hand, one can argue that our task was simpler both perceptually (alternatives are distinguishable by their size) and conceptually (only one variable —i.e., the size of alternatives— is relevant for performing successfully). In this same line, the task used by Mc Lean et al. (2020) may have not induced loss of information since it involved only one extra competing alternative compared to the classic 2-AFC tasks. Their result is inline with previous computational models applied to similar multialternative random dot motion tasks that explicitly take into account the evidence of each possible direction (Churchland et al., 2008; Niwa & Ditterich, 2008) —although see Experiment 4 in Yeon & Rahnev (2020). In short, although important, the amount of alternatives itself is not the only factor at play when considering how much information can reach decision and metacognitive levels in perceptual decision making. Further research is needed to evaluate the weight and interplay of these factors (stimulus complexity, task complexity, number of alternatives) on the loss of information in multialternative decisions.

Multiple empirical dissociations between metacognition and performance suggest that different information or information with different quality is available for metacognitive judgments such as confidence ratings (Fleming & Dolan, 2012). In this sense, some computational models explicitly suggest a separate line of evidence for metacognitive judgments (Mamassian, 2016; Mamassian & De Gardelle, 2022) and others propose a hierarchical structures where “type 2” judgments (e.g. confidence) evaluates the quality of the “type 1” (e.g. decision) information (Maniscalco & Lau, 2016). Our results are inline with these views as the Population + noise model underestimated the metacognitive sensitivity found in our data, specially in Experiment 2. As the model only has access to the information of the type 1 judgment for computing metacognitive sensitivity —a kind of “single-channel” model (Maniscalco & Lau, 2016)—, an upper bound for the predicted metacognitive ability is then established. Consequently, the higher metacognitive levels found compared to the model’s predictions suggest that confidence judgments had extra or different information than the one that supports type 1 judgments, resulting in a boosted metacognitive sensitivity. Indeed, on Experiment 2 there was not an association between performance in the second decision and metacognition, suggesting that participants that lost more sensory information to inform their decisions nevertheless had information to inform their metacognitive judgments. One limitation of this finding is that the AUROC-2 measure can be affected by task performance (Fleming & Lau, 2014; Maniscalco & Lau, 2012). Unfortunately, no alternative method has been developed yet to address metacognition independently of performance in multialternative decision tasks, and even methods that seem promising in controlling for performance confounds have been shown to fail with respect to that aim (Rahnev, 2023). Further research is needed to precisely evaluate metacognition independently of performance in multialternative decision tasks.

Previous research has suggested that confidence may ignore information of unchosen options and only rely on the evidence favouring the selected option, an effect termed “positive evidence bias” (Maniscalco et al., 2016; Zylberberg et al., 2012). While we did not test for this phenomenon here, our results suggest that this —possibly— neglected information of unchosen options can be later accessed by confidence judgments when humans are asked about a second guess, as confidence reports were informative about second decision performance. This means that although confidence can be biased by the evidence favouring the chosen option, the evidence against it does not remain inaccessible to metacognitive levels.

In conclusion, here we found that, although suboptimally, humans decision makers can retain information from unselected alternatives when facing a multi-alternative decision. Moreover, the metacognitive system can access this information as well. Our results suggest, however, that an exact copy of the sensory representation is not present at the decision and metacognitive level, as the model including noisy versions of the representations was the best fitting model to our data. These findings support previous multialternative models that assume that information from all alternatives is represented by human decision makers both for decisions and confidence computations.

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Open data and materials

All experimental data and the scripts that reproduce the reported results and figures are available at: https://osf.io/d5qyp/.

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