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Decisions Are Based on Less Information Than Metacognitive Judgments in Multialternative Contexts

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Humans often face decisions between multiple alternatives. In these contexts, some evidence suggests that only the alternative with the highest evidence is represented by the decision system. However, other findings indicate that unchosen alternatives' information remains available for decision computations. To evaluate how much information from unchosen alternatives is accessible by the decision system, we employed a second-guess paradigm: When participants selected an incorrect alternative, they were given a second opportunity to make a new choice. By fitting computational models to data from two preregistered experiments involving four (Experiment 1) and 12 (Experiment 2) alternatives, we found evidence for an intermediate position: After the first decision is made, noise corrupts the evidence from the initially unchosen options, suggesting that the decision system cannot access all the sensory evidence available to perform a second decision. We extended this finding by fitting the models to two previously published data sets involving different stimuli and numbers of alternatives (six and three) and found concordant evidence. In addition, we also evaluated the amount of information accessible by the metacognitive system, responsible for monitoring our behavior and reflecting upon the correctness of our decisions. We found that incorporating a separate channel of evidence unaffected by noise for metacognitive computations improves model fitting, suggesting that the decision system accesses less evidence than the metacognitive system. These results reconcile previous conflicting findings in multialternative decisions and highlight a dissociation between decision making and metacognition, offering new insights into the fundamental constraints of decision processes and the relative robustness of metacognitive evaluations.

Keywords: perceptual decision making, metacognition, confidence, multialternative decisions, computational modeling

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Guillermo Solovey and Pablo Barttfeld are last authors. The authors' experiments were preregistered on the Open Science Framework at https://doi.org/10.17605/OSF.IO/9W6JU. The data and scripts that reproduce the reported results are available at https://osf.io/d5qyp/. This work has not been published elsewhere. A preprint of this work was posted on PsyArXiv at https://osf.io/preprints/psyarxiv/byjv6_v1. Parts of this work have been shared through conference presentations.

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Perceptual decision making, that is, decisions human observers make about sensory information (Hanks & Summerfield, 2017; Heekeren et al., 2008), has been extensively studied through 2-alternative forced choice (2-AFC) tasks in which observers should commit to a decision between two competing options. Empirically driven computational models suggest that in these tasks, human decision makers take into account the evidence (i.e., the sensory information that supports one option over the other) for each of the two competing alternatives, and the decision aligns with the alternative with the highest evidence (Shadlen & Kiani, 2013). Successful examples of this approach are Signal Detection Theory models, which offer insights on the discrimination ability of an observer as well as her bias for one alternative or another (Macmillan & Creelman, 2005; Wixted, 2020), and Drift Diffusion models, which also include response time (RT) predictions (Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008). Moreover, these frameworks can account for the feeling of confidence of being correct that naturally accompanies every decision (Hellmann et al., 2023; Mamassian, 2016; Pleskac & Busemeyer, 2010).

However, many real-world decisions are not binary, and, importantly, some phenomena only arise in more complex decision settings. This is the case, for example, of contextual effects where the preference for some option is changed after the inclusion of other alternatives (Huber et al., 1982; Simonson, 1989; Tversky, 1972). Critically, these effects have been found also in the perceptual domain (Trueblood et al., 2013), suggesting they are a fundamental feature of human decision making that cannot be captured in 2-AFC tasks. Consequently, there is a growing interest in understanding the nuances of multialternative decisions (Busemeyer et al., 2019; Churchland et al., 2008; Rahnev et al., 2022; Turner et al., 2018), which are thought to reflect more naturalistic scenarios than 2-AFC paradigms (Yeon & Rahnev, 2020).

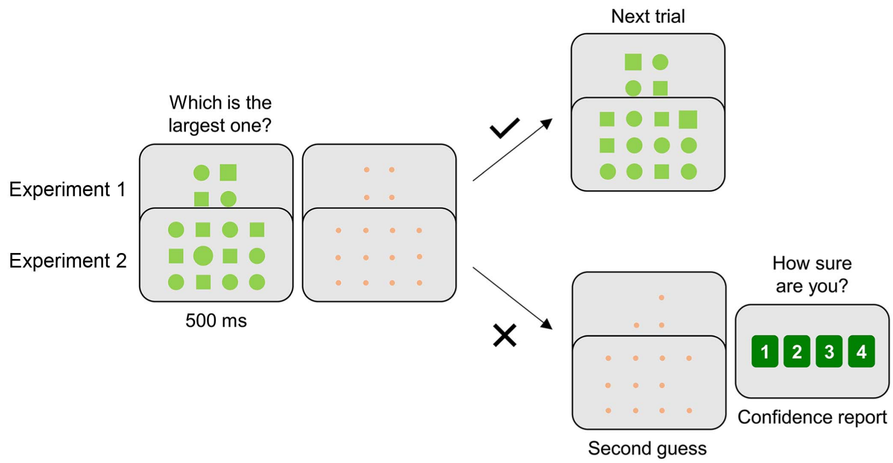
A key question in multialternative decision making is whether humans hold individual representations of all available alternatives—an assumption of virtually all computational models of decision making—or, alternatively, they create an abbreviated representation that only encodes the most subjectively salient or valuable stimuli. This issue highlights the concept of evidence availability, which refers to how accessible or usable sensory information is to the decision system. While it is reasonable that in simple 2-AFC tasks the two competing alternatives can be represented by the decision system, a recent study using multialternative tasks found evidence for a "summary" model, where only the information from the chosen alternative is included in the decision representation (Yeon & Rahnev, 2020). This result suggests that the decision system does not replicate the sensory information exactly, implying a suboptimal use of information in perceptual decision making. However, another study involving multialternative decisions found evidence that the decision system has access to the evidence from unselected alternatives (McLean et al., 2020)—a result in line with previous multialternative studies that modeled the decisions assuming a competition within the decision system among the evidence for each alternative (Busemeyer et al., 2019; Churchland et al., 2008; Dumbalska et al., 2020; Niwa & Ditterich, 2008; 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 unexplored. Traditionally, metacognition is evaluated by asking participants how confident they are in their decision accuracy (Fleming & Lau, 2014). In scenarios where only the chosen alternative's evidence is encoded, this evidence alone might serve as a basis for confidence judgments. However, recent studies in multialternative decision making suggest that evidence from unchosen alternatives can also influence this metacognitive feeling of confidence. For instance, using a decision task with three competing alternatives, Li and Ma (2020) found that confidence was best explained by the difference in the probability of being correct of the two best options, and Comay et al. (2023) found that, in some contexts, when two competing options are next to clearly incorrect alternatives, confidence increases without affecting decision accuracy or RTs. While at first glance these findings seem to challenge a summary encoding—where only the chosen option evidence influences confidence—these results are not entirely inconsistent, as previous metacognition models suggest a separate route of evidence for metacognitive computations (known as "dual-channel" models of metacognition; Mamassian, 2016; Mamassian & de Gardelle, 2022, 2025; Maniscalco & Lau, 2016), which could lead to dissociations between the information used by the decision system and by the metacognitive system (Fleming & Dolan, 2012).

To clarify the nature of the multialternative decision and metacognitive representations, we carried out two preregistered experiments that varied the number of alternatives. We put to test three computational models with different degrees of information loss. We tested these models against data from our experiments and two previously published data sets involving different stimuli (from McLean et al., 2020; Yeon & Rahnev, 2020). All experiments employed a "second-guess" paradigm (McLean et al., 2020, and Experiment 3 in Yeon & Rahnev, 2020; Figure 1). In our task, 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. This paradigm is useful to study to what extent a decision maker has knowledge about initially unchosen options (McLean et al., 2020). Indeed, if no evidence from initially unselected options is available at the decision stage (i.e., summary encoding), then chance-level performance should be found in these second judgments. If, however, evidence from initially unselected options can access the decision stage, performance should exceed chance levels. In addition, participants 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 evidence from unchosen alternatives is accessible by both the decision-making and metacognitive levels, as participants were able to give meaningful second decisions and confidence judgments about those decisions. However, the information accessed at each level is not identical: Interestingly, less information reaches the decision system compared to the metacognitive level. We found that behavior is best captured by a model where the evidence that accesses the decision system for performing second guesses is corrupted by noise—implying a loss of the initial information, which was consistent in all data sets. However, a dual-channel version of this model where the metacognitive channel is not corrupted by this noise fits the data substantially better, meaning that, as mentioned, the decision system loses more information than the metacognitive system.

Figure 1
Size Discrimination Task



Note. We employed a "second-guess" experimental paradigm: Experiments consisted of a size discrimination task where participants had to identify the largest geometrical shape within a set of four alternatives (Experiment 1) or 12 alternatives (Experiment 2). If the decision was correct, the next trial began automatically. Otherwise, participants had a new chance to choose which figure was the largest (critically, stimuli did not appear again on screen). After this second guess, participants reported their confidence in being correct on a 4-point scale. See the online article for the color version of this figure.

Method

Experiments were 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 and National Scientific and Technical Research Council—Córdoba, Argentina). Experiments were preregistered at https://osf.io/9w6ju.

Participants

Eighteen participants took part in Experiment 1 (13 females; $M_{\text{age}} = 24.5$, $SD_{\text{age}} = 3.37$) and in Experiment 2 (14 females; $M_{\text{age}} = 23.78$, $SD_{\text{age}} = 2.94$). Sample size was calculated using the G*Power software to reach >80% power to detect a significant difference in the *t* tests performed (see the preregistration 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

Data collection was conducted locally in experimental rooms dedicated to this purpose. Experiment 1 (Figure 1) involved a 4-alternative perceptual decision-making task. Participants sat 81 cm 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 800 ms, followed by a stimuli array consisting of geometrical shapes (squares and circles) in a 2 × 2 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 1/3, since it is made on three 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 one-up/one-down 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.

Experiment 2 (Figure 1) was identical to Experiment 1 but with 12 instead of four alternatives. The procedure was exactly the same as in Experiment 1: Participants sat 81 cm from the screen and completed two sessions of 360 trials each on two different days. Figures were displayed on a 3×4 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 $1/11$ since 11 alternatives are left for the second judgment.

Data Analysis

We excluded trials with RTs larger than 8 s or shorter than 150 ms on any of the responses (first and second decisions 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 α 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–2 (Fleming & Lau, 2014).

We used one-tailed t tests to compare the second decision performance and the metacognitive sensitivity level to chance levels ($1/3$ for second guesses in Experiment 1, $1/11$ for second guesses in Experiment 2, and $1/2$ for metacognition). 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 preregistered and can be found at https://osf.io/9w6ju.

Computational Modeling

We fitted the data from our experiments, McLean et al.'s (2020) data, and Yeon and Rahnev's (2020) Experiment 3 data (note that we do not include model fitting results from Yeon and Rahnev's Experiments 1, 2, and 4 since their design does not allow the recovery of the Population + Noise model; see the Supplemental Material). In Experiment 3 from Yeon and Rahnev's study, participants ($N = 10$) had to decide which among six symbols was presented more times in a 7×7 array of symbols presented for 500 ms. In 40% of the wrong responses, a second opportunity to decide was given to the participants. In McLean et al.'s tasks, participants ($N = 7$) faced a random dot motion task between three different directions and had to choose which direction the majority of the dots moved. Participants were told to report an additional second guess after each decision. Participants could watch the stimuli as long as they wanted, up to 5 s. Further details of the experimental designs can be found in the original publications.

We compared three different computational models to evaluate different possible information processing scenarios regarding the evidence available in multialternative perceptual decision making. Each model points to a different degree of loss of information (Figure 2). All models start similarly: On each trial, random samples (one for each alternative, indexed by i) are generated from a Gaussian distribution with mean μ_i and standard deviation σ. Formally,

$$x_i \sim N(\mu_i, \sigma), \tag{1}$$

where $i \in \{1, 2, \ldots, n\}$, and n represents the number of alternatives available. While μ_i are fixed, σ is fitted to each participant by maximizing its log-likelihood. Note that in our experimental design, μ_i is 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. In Yeon and Rahnev's (2020) design, μ_i is fixed at 1 for the largest alternative and at .9 for the rest of the alternatives. In McLean et al.'s (2020) design, μ_i is fixed at the coherence value used in the random dot motion task.

The first decision, d_1, corresponds to the alternative associated with the highest sample obtained.

$$d_1 = \text{argmax}(x_i). \tag{2}$$

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 nonchosen alternatives, leading to both a random decision and a random confidence level. This can be stated as that any option has an equal probability of being selected for the second decision:

$$P(d_2 = 1) = P(d_2 = 2) = \ldots = P(d_2 = n) = \frac{1}{n}, \tag{3}$$

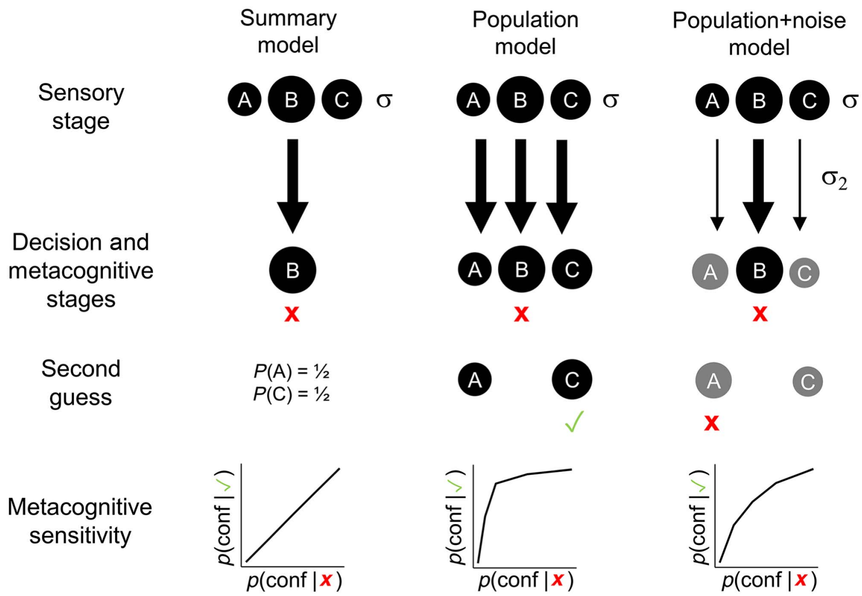
where d_2 refers to the second decision. For fitting Experiment 3 of Yeon and Rahnev (2020), we also tested the *Summary + Strategic Choice* model (proposed by Yeon & Rahnev, 2020), where participants remember one random nonchosen symbol from the stimuli array and choose its category in the second-guess stage instead of randomly picking any of the initially nonselected alternatives. In Yeon and Rahnev's experiment, the dominant symbol was presented 14 times and the nondominant symbols seven times each. Under this scenario, for a second judgment, participants will pick the correct option 33.3% of the time, since there are 42 locations left and the dominant symbol is present 14 times, that is, $14/42 = 33.3\%$. Similarly, each of the remaining incorrect options is picked 16.7% of the time, that is, $7/42 = 16.7\%$. In both models (Summary and Summary + Strategic Choice), the predicted confidence for a specific trial was equal to a random value sampled from a uniform distribution between 0 and 1.

Population Model

The population model proposes that at the decision instance, the activity of all the alternatives is represented and sustained until the

Figure 2

Computational Models and Their Predictions



Note. We compared three models with different degrees of information loss. Assuming a choice between three alternatives ("A," "B," and "C"), the summary model proposes that only the evidence of the alternative with the highest activation ("B" in the example, as illustrated by its larger size) reaches the decision and metacognitive stages. The population model proposes that information that reaches the decision and metacognitive systems is an exact copy of the sensory information. The Population + Noise model lies between the two, proposing that noisy evidence (with noise controlled by an extra parameter: σ_2) from initially unchosen options reaches decision and metacognitive systems. According to the summary model, no evidence from initially unchosen options is present at the decision level; therefore, if an initial decision is incorrect and a second judgment is solicited, then decision and metacognitive performance in this second guess should be at chance level, as no information from initially unchosen options is available. The population and Population + Noise models, however, predict above-chance levels in both second decisions and metacognitive performance, as information from unchosen options can reach the decision and metacognitive systems. Moreover, higher second-guess performance and metacognitive sensitivity are predicted by the population model when compared to the Population + Noise model, as this model is the model with the highest information available. conf = high confidence. See the online article for the color version of this figure.

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 the maximum out of all previously nonselected options (i.e., the second highest sample overall). Formally,

$$d_2 = argmax(x_i). \quad (4)$$

In the latter, and also in the confidence models stated below, $i \in \{1, \ldots, n\} \setminus \{d_1\}$. The notation $\setminus \{d_1\}$ means that the value after the backslash is not included in the set, thus representing that the option chosen in the first judgment is not available to be selected for a second judgment. Confidence on this second decision under this model can have several mappings. We tested four of them. For the first one, confidence can reflect the level of activation of the alternative chosen ("Max model"; Zylberberg et al., 2012):

$$conf = \max(x_i). \quad (5)$$

In the second model version, confidence is equal to the difference between the two highest activations ("Balance of evidence model"; Li & Ma, 2020; Mamassian, 2016; Reynolds et al., 2020; Vickers, 1979):

$$conf = \max(x_i) - \max(\{x_i\} \setminus \{\max(x_i)\}). \quad (6)$$

In the third model, confidence reflects the sum of the differences between the highest activation and the rest ("Contrast model"; Comay et al., 2023). Assuming that alternative one is the one associated with the highest sample, the model can be stated as follows:

$$conf = (x_1 - x_2) + (x_1 - x_3) + \ldots + (x_1 - x_n). \quad (7)$$

Finally, for the last tested mapping, confidence represents the difference between the activation of the chosen alternative and the mean of the rest of the activations ("Average-residual model"; Comay et al., 2023):

$$conf = \max(x_i) - \frac{\sum\{x_i\} \setminus \{\max(x_i)\}}{n-1}. \quad (8)$$

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. Let us define the corrupted samples for each alternative as y_i, where $i \in \{1, \ldots, n\} \setminus \{d_1\}$. Then, this process can be represented as follows:

$$y_i \sim x_i + N(0, \sigma_2), \quad (9)$$

where 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, but taking as argument y_i instead of x_i. We also tested a dual-channel version of the Population + Noise model where x_i are used for confidence computations (thus, metacognition is computed similarly as in the population model) and a model with independent noise for confidence judgments.

In order to compute metacognitive sensitivity in the size discrimination tasks, 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 area under a receiver operating characteristic curve–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 2,000 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 calculated 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 parameter values using the binomial data model and the previously calculated probabilities using the *dbinom* function in R. We followed a similar procedure to fit Yeon and Rahnev's (2020) and McLean et al.'s (2020) data by simulating 30,000 trials to approximate the probabilities of being correctly predicted by the models. To model metacognitive sensitivity (only in our experiments), 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 ran three 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 a mean of zero and a 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.

For the dual-channel version of the Population + Noise model, we allowed confidence judgments to be made with the alternative evidence before being corrupted by σ_2. For the dual-channel version with metacognitive noise (Bang et al., 2019; Boundy-Singer et al., 2023; Mamassian & de Gardelle, 2022; Shekhar & Rahnev, 2021), we added an extra noise parameter σ_3, which corrupted the information in the metacognitive channel (i.e., the information for computing confidence). The results of the dual-channel version with metacognitive noise are reported in the Supplemental Material.

Parameter Recovery

We ran a parameter recovery analysis and found that our method was able to recover the true parameter values. We obtained significant Pearson correlations between the true and the recovered parameters of 0.80 ($p < .001$), 95% confidence interval (CI) [0.71, 0.86], $df = 98$, for the σ parameter; to 0.36 ($p < .001$, 95% CI [0.17, 0.52], $df = 98$) for the σ_2 parameter; and to 0.32 ($p = .001$, 95% CI [0.14, 0.49], $df = 98$) for the β parameter.

Model Comparison

We compared the performance of the models by using the Bayesian information criterion (BIC). The formula used for the BIC was as follows:

$$\mathrm{BIC}_i = k \log(n) - 2 \log(L_i), \quad (10)$$

where k is the number of free parameters (two for the summary and population model, three 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. We summed the BIC across subjects.

Transparency and Openness

We report all data exclusions (if any), all manipulations, and all measures in the study. We also report, in the preregistration (https://doi.org/10.17605/OSF.IO/9W6JU), how we determined the sample size for our experiments. All data and analysis code that reproduce the present results are available at https://osf.io/d5qyp/. As mentioned, experiments and their associated data analysis were preregistered. Computational models, model fitting, and model comparison metrics were also preregistered. The dual-channel versus single-channel comparison was exploratory.

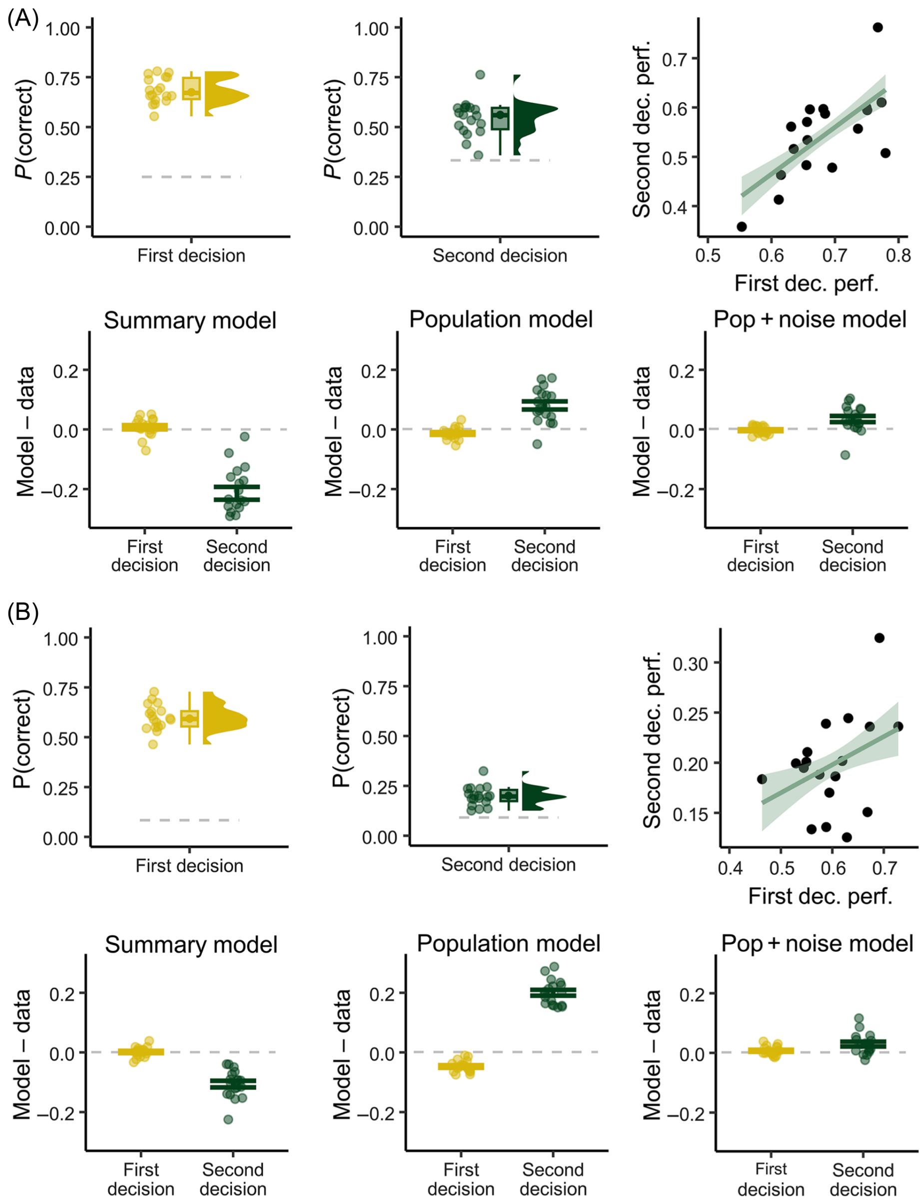
Results

Behavioral Results

In Experiment 1, participants had a mean performance for the first decision of 0.68 (SD = 0.06; Figure 3A). Importantly and as

Figure 3

Size Discrimination Task: Behavioral and Model Fitting Results



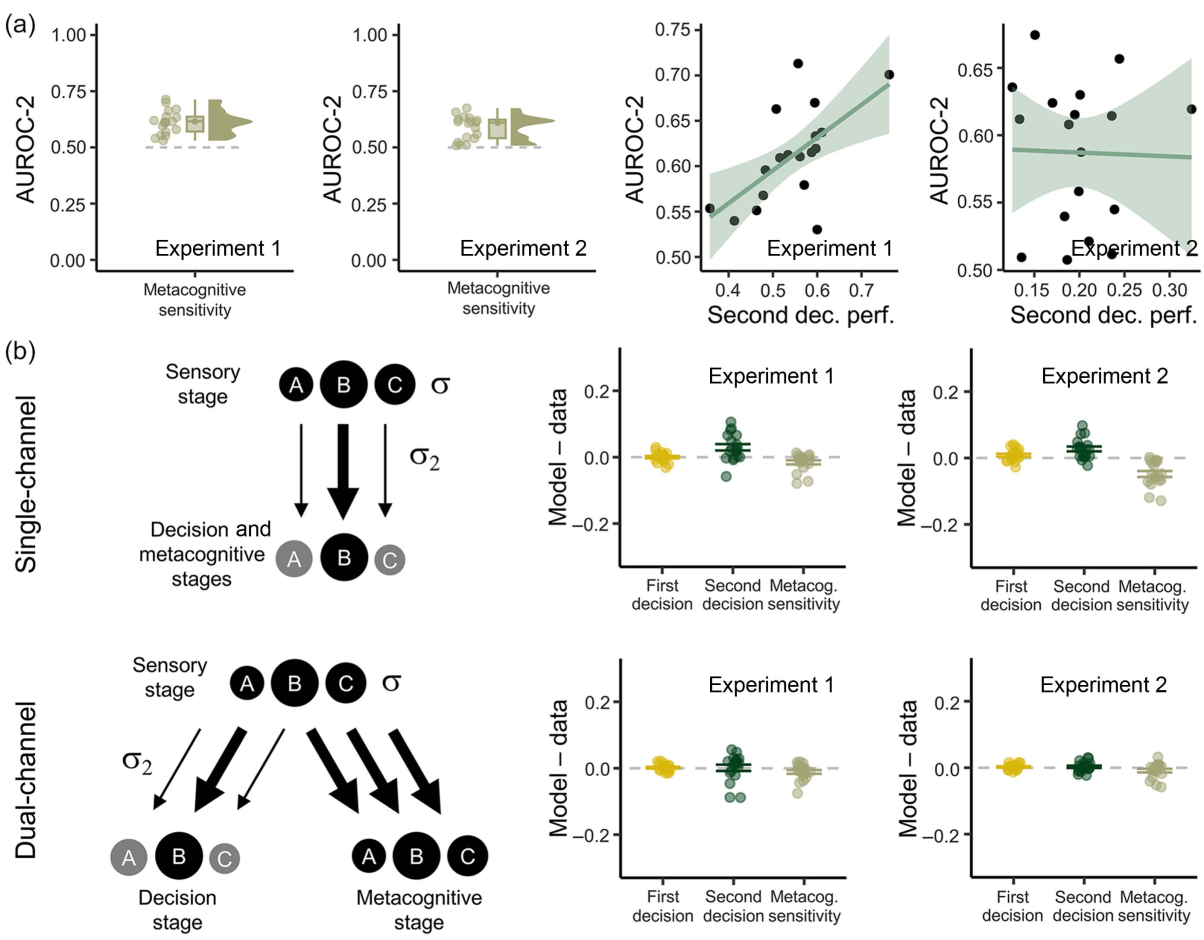
Note. (A) Experiment 1 (four alternatives) results. Participants were above chance in both first and second decisions (chance level is illustrated with the gray dotted line). Moreover, an increase in first decision performance significantly predicted an increase in second decision performance (first row). Regarding the models' predictions (second row), while accurately predicting the performance on the first judgment, the summary model underestimated the second decision performance. In contrast, both the population model and the Population + Noise model fitted the data better, with the population model overestimating more the second decision performance. (B) Experiment 2 (12 alternatives) results. Similar to the results of Experiment 1, participants were above chance in both first and second decisions. However, an increase in first decision performance did not predict an increase in second decision performance (first row). With respect to the models' predictions, the summary model again underestimated participants' performance on the second decisions. Illustrating a greater loss of information due to the increased number of alternatives, the population model was the worst fitting model in this second experiment, underestimating first decision performance and largely overestimating second decision performance. The Population + Noise model was the best fitting model, accurately predicting first and second decision performance. In this and all figures, dots represent individuals, and error bars represent the standard error of the mean. Also note that the version depicted here (and in Figure 4) for the Population + Noise model is a "single-channel" version of this model (Figure 5 shows the results for a "dual-channel" version, where a separate channel for computing metacognition is included). dec. = decision; perf. = performance; Pop = population. See the online article for the color version of this figure.

predicted in the preregistration, participants showed above-chance second decision performance, $t(17) = 10.03$, $p < .001$, $d = 2.36$, $M = 0.54$, 95% CI [0.51, Infinite], Figure 3A, and also above-chance metacognitive sensitivity, $t(17) = 8.92$, $p < .001$, $d = 2.10$, $M = 0.61$, 95% CI [0.59, Infinite], Figure 4A. We also explored how these variables relate to each other. We found that first decision performance significantly predicted performance in the second decision, $F(1, 16) = 14.5$, $\beta_{\text{first decision}} = 0.95$, 95% CI [0.46, 1.44], $p = .002$, $R^2 = .44$, Figure 3A, and second decision performance significantly predicted metacognitive sensitivity, $F(1, 16) = 9.48$, $\beta_{\text{second guess}} = 0.36$, 95% CI [0.12, 0.60], $p = .007$, $R^2 = .33$, Figure 4A.

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 3B). Participants again showed above-chance second-guess performance, $t(17) = 9.40$, $p < .001$, $d = 2.22$, $M = 0.20$, 95% CI [0.18, Infinite], Figure 3B, and also above-chance metacognitive sensitivity, $t(17) = 6.89$, $p < .001$, $d = 1.62$, $M = 0.59$, 95% CI [0.57, Infinite], Figure 4A. Note that, as predicted due to a larger loss of information associated with a larger number of alternatives, effect sizes were smaller in this experiment. Exploring the relationship between the variables, we found that—contrary to Experiment 1 results—performance on the first decision did not predict second decision performance, $F(1, 16) = 2.62$, $\beta_{\text{first decision}} = 0.28$, 95% CI [−0.05, 0.61], $p = .12$, $R^2 = .09$, Figure 3B, and performance on the second decision did not predict metacognitive sensitivity, $F(1, 16) = 0.01$, $\beta_{\text{second guess}} = -0.03$, 95% CI [−0.58, 0.52], $p = .92$, $R^2 = -.06$, Figure 4A.

Figure 4

Behavioral and Model Fitting Results in Metacognitive Sensitivity



Note. (A) Behavioral results. As predicted, metacognitive sensitivity was above chance in both experiments, suggesting that information from initially unchosen options can reach the metacognitive level. Participants with higher second decision performance also had higher metacognition in Experiment, 1 but, interestingly, this relationship was not present in Experiment 2. (B) A dual-channel (second row) architecture that allows for a separate route of evidence where unchosen options' information is not corrupted by σ_2 fits the data substantially better than a single-channel model (first row). These results are evidence that the decision system accesses less information than the metacognitive system. Interestingly, allowing for a separate route of evidence for metacognitive judgments also made the model's predictions regarding second-guess performance more accurate, as the model did not need to overestimate accuracy to achieve higher metacognitive levels. AUROC-2 = area under a receiver operating characteristic curve–2. dec. = decision; perf. = performance. See the online article for the color version of this figure.

Computational Modeling

Predicting Second Decision Performance

Our model fitting results suggest that while the summary model underestimated second decision performance, the population model overestimated it. On the other hand, the Population + Noise model could better capture participants' behavior in the two experiments (Figure 3A and 3B, bottom rows). By comparing the models using the BIC to correct for the number of parameters, we found that the population model was the best model in Experiment 1, and the Population + Noise model was the best model in Experiment 2 (Table 1; although note that the population model loses against a dual-channel version of the Population + Noise model). Importantly, and in line with our prediction that more information will be lost when more alternatives are involved, the population model was the worst fitting model in Experiment 2.

We then extended our results by fitting the models to two previously published data sets that also employed a second-guess paradigm (McLean et al., 2020; Yeon & Rahnev, 2020). Regarding McLean et al.'s (2020) data, we again found that the Population + Noise model was the best fitting model (Table 1 and Figure 5A). In Yeon and Rahnev's (2020) data, we found that another model with intermediate loss of information, the Summary + Strategic Choice model, was the best fitting model, closely followed by the Population + Noise model (Table 1 and Figure 5B). The pattern of the results was similar to the previous experiments: While the summary model underestimated second-guess accuracy, the population model overestimated it. On the other hand, the Population + Noise model could capture the behavior of the participants in both the first and second decisions. Combining all the data sets together, the Population + Noise model is selected as the best fitting model (Table 1).

Comparing Single-Channel and Dual-Channel Models for Metacognition

The modeling results suggest that unchosen options evidence accesses the decision system but in a suboptimal manner, as this evidence is corrupted by noise. To explore and evaluate whether the metacognitive system suffers the same loss of information, we compared the predictions of a single-channel and a dual-channel version of the Population + Noise model. Specifically, in this implementation of the dual-channel model, it is assumed that confidence evidence—from which metacognition is computed—has a separate channel of evidence that is not corrupted by σ_2. The modeling results suggest that this model architecture fits the data from both experiments significantly better than the single-channel version (Table 1 and Figure 4B).

Discussion

In the present work, we have studied the multialternative representations that sustain decision making and metacognition. The underlying motivations were that contradictory results were found regarding the amount of information accessible for decision computations (McLean et al., 2020; Yeon & Rahnev, 2020), and moreover, there was an open question about whether this—or different—information reaches 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 a decision system accessing an exact copy of the sensory information to perform a second judgment 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. In addition, the metacognitive system seems to not be subject to such limitations, as a dual-channel version of the mentioned model fitted the data substantially better. In this implementation, the channel of evidence for confidence judgments did not include extra noise, therefore not underestimating the metacognitive ability of the participants.

This suboptimal use of information by the decision system at the second-guess stage is found not only in our experiments but also in two previously published data sets involving different stimuli. Importantly, even in not-so-complex decisions between three (McLean et al., 2020) or four alternatives (our Experiment 1), some information is lost. The findings in McLean et al. (2020) are particularly notable since this experiment not only has only one extra alternative compared to classic 2-AFC tasks, but participants could see the stimuli for up to 5 s, allowing ample time to retain the sensory evidence. Therefore, this suboptimal use of information for second judgments in multialternative decisions seems to be a fundamental limitation of the decision system (Yeon & Rahnev, 2020). As Yeon and Rahnev (2020) suggest, an exact copy of the sensory information

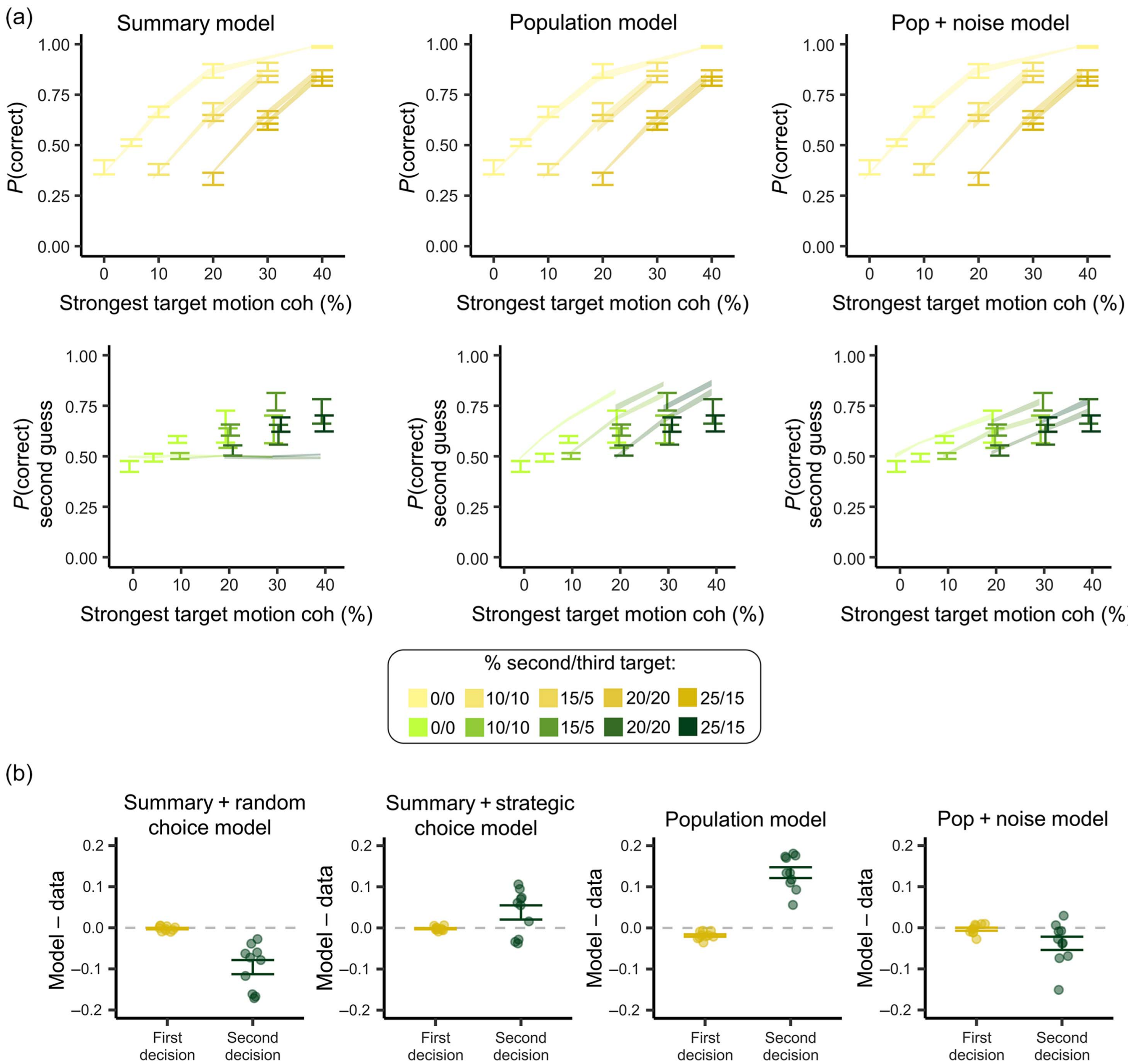
Table 1
BIC Model Comparison

Dataset	Summary model	Population model	Population + Noise model
Experiment 1	1,274.89	455.63	494.01 (**454.20**)
Experiment 2	911.03	1,141.99	546.12 (**445.09**)
McLean et al. (2020)	1,333.09	1,304.02	**1,166.84**
Yeon and Rahnev's (2020) Experiment 3	528.66 (**336.14**)	652.57	396.02
All data (summed BIC)	4,020.67 (3,828.15)	3,554.21	2,602.99 (**2,462.15**)

Note. The winning model has its BIC value in bold. Values in parentheses under the summary model reflect the fit of the Summary + Strategic Choice model. Values in parentheses under the Population + Noise model reflect the fit of the dual-channel version. BIC = Bayesian information criterion.

Figure 5

Model Fitting Results to (A) McLean et al.'s (2020) Data and (B) Yeon and Rahnev's (2020) Experiment 3 Data



Note. The three models accurately predicted first decision behavior. However, the summary model greatly underestimates second decision performance, and the population model consistently overestimates it. The Population + Noise model accurately predicts both first and second decisions. Interestingly, the Summary + Strategic Choice model was the best fitting model in the data from Yeon and Rahnev (2020), suggesting that the loss of information is stronger in that experiment. In Panel A, shaded regions represent the standard error of the mean of the models' predictions. coh = coherence; Pop = population. See the online article for the color version of this figure.

may be present in more automated processes—such as multisensory integration—or in simple 2-AFC tasks, but for multialternative explicit decisions, the decision-making circuits cannot retain all the available information.

How much information is lost can depend on a multitude of factors, not just the number of alternatives. In the visual domain, Rosenholtz (2020) indicated 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. For instance, Experiment 3 from Yeon and Rahnev's (2020) study involves more complex stimuli (symbols) whose information can already be lost in peripheral encoding as the distinction of features that requires binding usually needs selective attention (Rosenholtz, 2016, 2020). Moreover, this task has considerable decision complexity as it involves both recognizing each individual stimulus and estimating their frequency while taking into account the frequency of the other stimulus categories. In comparison, one can argue that our size discrimination task is 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 sense, further research could take advantage of the extra noise parameter of the Population + Noise model, which can be useful to quantify which task factor (e.g., stimulus complexity, number of alternatives, task demands) is inducing more or less information loss in the decision system. This extra noise parameter can also be useful to quantify individual differences in the capacity limits of the decision system.

One might argue that this second-guess design is not a fair test for the summary model, as participants can in principle quickly make two decisions and, in case of being asked for a second guess, report their second choice. While this cognitive strategy is in principle possible, model recovery analysis suggests that this second-guess design was the best to capture the hybrid possibility proposed by the Population + Noise model (see the Supplemental Material). Despite this cognitive strategy possibility, our results still point out that this second judgment is performed suboptimally, in agreement with the summary model.

In the present study, participants' behavior was captured by a "static" model where only one piece of evidence is relevant to make the decision. A dynamical extension of this approach can be achieved with drift-diffusion models (Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008), which propose that evidence is accumulated over time up to a threshold, and, when reached, the decision is made. An advantage of the diffusion framework is that not only can decisions be predicted, but also the time at which the decision is made. This difference—and others, such as the number of parameters—could in principle explain why McLean et al. (2020) did not find information loss in their data set using a dynamic model. In contrast, using a static model, we observe information loss. Further research could extend the Population + Noise model in order to incorporate evidence accumulation processes to compare the models and the degree of information loss in the McLean et al. data set more precisely. Indeed, having to fit not only decisions but also RTs represents an additional constraint to the possible mechanisms that can account for the data. Moreover, evidence accumulation frameworks are also able to predict confidence. For instance, Reynolds et al. (2020) implemented the balance-of-evidence hypothesis (Li & Ma, 2020; Mamassian, 2016; Vickers, 1979) in an evidence accumulation framework by adding extra thresholds to the losing accumulator in the case of binary choices. For example, considering the case where only two confidence responses are allowed (high vs. low), one threshold is added to divide high- versus low-confidence reports. If the losing accumulator ends below the threshold, then the balance of evidence is higher, and therefore, confidence is high. Extensions to several discrete confidence levels, such as one to four as in the present study, are possible by adding more thresholds. Although developed in the context of 2-AFC, this idea could be extended for predicting confidence in multiple alternatives in a dynamic framework by, for instance, adding multiple accumulators and evaluating the balance-of-evidence state between the winning and second-best accumulators.

Another possible explanation for our results is that in all experiments there was a goal set by the experimenters before stimuli presentation (i.e., choose the largest option, the item presented most often, or the direction where the majority of dots are moving). As attention depends on the task's goal (Sepulveda et al., 2020), participants could look for the goal-consistent option and only retrieve information from other options encoded during this search. Next, they use all of this information for a second judgment if needed. Such a mechanism would produce similar predictions as the Population + Noise model and the Summary + Strategic Choice model. Further research could include gaze data to check if the options that were fixated on most during the initial search are the ones that are most chosen in a second judgment, thereby supporting this specific mechanism.

Traditionally, perceptual decision making and metacognition have been studied using 2-AFC 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). How do our results impact this notion? Our results suggest that this assumption extends to multialternative decisions, as even in a 12-alternative decision-making task, human observers can, although suboptimally, recover information from unchosen options. The fact that—although noisy—information from unchosen alternatives accesses the decision stage is also in line with previous multialternative work (Churchland et al., 2008; Li & Ma, 2020; McLean et al., 2020; Niwa & Ditterich, 2008) and with several contextual effects that arise in multialternative decision-making tasks both in decisions (Busemeyer et al., 2019; Trueblood et al., 2013) and in confidence judgments (Comay et al., 2023; Miyoshi & Sakamoto, 2024). As most computational accounts of these empirical results rely on the assumption that information of all alternatives is available and combined in a specific way (Busemeyer et al., 2019; Comay et al., 2023; Dumbalska et al., 2020; Li & Ma, 2020; Niwa & Ditterich, 2008; Turner et al., 2018), the evidence reported here is then critical to sustain those explanations.

A related current discussion is whether the same circuits that encode information for choice also, and at the same time, encode information that is read out to convey confidence judgments. The evidence in favor of circuit sharing mostly comes from experiments in macaques that show that the same neurons that are thought to encode choice formation also, and at the same time, affect confidence (Kiani et al., 2014; Kiani & Shadlen, 2009). However, if confidence is merely encoded in the same circuitry as choice, it is unclear how there are several experiments that show clear dissociations between decision accuracy and confidence (Graziano et al., 2015; Graziano & Sigman, 2009; Maniscalco & Lau, 2016; Zylberberg et al., 2014). In this sense, some computational models explicitly suggest a separate line of evidence for metacognitive judgments such as confidence ratings (Mamassian, 2016; Mamassian & de Gardelle, 2022, 2025), and others propose hierarchical structures where "Type 2" judgments evaluate the quality of the "Type 1" (e.g., decision) information (Maniscalco & Lau, 2016). Our results are in line with these views as the single-channel version of the Population + Noise model underestimated the metacognitive sensitivity found in our data, especially in Experiment 2. As this model implementation only has access to the information of the Type 1 judgment for computing metacognitive sensitivity, 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 different information than the one that supports Type 1 judgments, resulting in a boosted metacognitive sensitivity. This is sustained by the fact that a dual-channel version of the Population + Noise model fits the data significantly better and does not underestimate metacognition. In other words, our results suggest that the decision system has access to less information compared to the metacognitive one. Moreover, as the information that accesses the latter is not corrupted by noise, it can be considered that the metacognitive system is less suboptimal than the decision system in multialternative choices. Also note that we are framing our findings as indicating that the decision system has less information than the metacognitive system—and not that the latter has more information than the former—since we are not including extra information for confidence computations, as, for instance, it has been done in models with postdecision evidence accumulation (Moran et al., 2015; Navajas et al., 2016; Yu et al., 2015). Instead, we assume that the information available to the metacognitive system is not corrupted. Nevertheless, it is possible that a model with this kind of extra information could account for the dissociation found here, as we are asking for confidence once the second judgment has been made, allowing for postperceptual processes to add information that increases metacognitive accuracy. Changing the ordering of decision and confidence reports or obtaining both measures simultaneously could be a way to test whether the reported dissociation is due to postperceptual processes (Matthews & Shibata, 2024).

Several models have been proposed that include metacognitive noise (i.e., noise that specifically corrupts the metacognitive channel of information; Bang et al., 2019; Boundy-Singer et al., 2023; Mamassian & de Gardelle, 2022; Shekhar & Rahnev, 2021). In line with this, we also tested a dual-channel version of the Population + Noise model with metacognitive noise, but we found that this model variation did not outperform the noiseless dual-channel version (see the Supplemental Material). This suggests an interesting difference between multialternative scenarios and the classic 2-AFC tasks where the models with metacognitive noise have been developed. We nevertheless advise caution in interpreting this finding given that the experimental design conceived here did not aim to test for the presence of noise in confidence computations. Indeed, with experiments designed for detecting the effects of metacognitive noise, its presence is completely justified (Bang et al., 2019).

In line with the idea of different sources of information for Type 1 and Type 2 judgments, in 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 area under a receiver operating characteristic curve–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 in 2-AFC tasks have been shown to fail with respect to that aim (Rahnev, 2025). Further research is needed to precisely evaluate metacognition independently of performance in multialternative decisions.

Another limitation regarding our findings in the metacognitive domain is that we used a discrete, 4-point scale to acquire confidence judgments. While restricting confidence options up to four levels makes the scale easy to use for participants, recent theoretical work suggests that continuous response paradigms can provide additional information about the decision-making process, and furthermore, this extra information can help to constrain the space of possible models that can account for the data (Rasanan et al., 2024). Indeed, while discrete choices have a natural limitation on the information they provide given the number of response options available, continuous response metrics provide a theoretically unlimited amount of information about the choice process (although practically this information is limited by the precision of the decision maker). Further research could replicate our studies but employ a continuous scale for confidence judgments to evaluate whether the reported effects here do not depend on the reporting scale used.

In conclusion, here we found consistent evidence for a suboptimal use of unchosen options' information by the decision system in multialternative decisions. Moreover, the decision system appears to access less information than the metacognitive system, as a model without noise corrupting the evidence that reaches the metacognitive stage fitted the data significantly better. Our results serve to reconcile previous contradictory findings in multialternative decisions by proposing a model with an intermediate degree of loss of information and further expand on them by incorporating a model for the metacognitive system.

Constraints on Generality

The data sets analyzed in this study were collected from labs across both the northern (McLean et al., 2020; Yeon & Rahnev, 2020) and southern (our experiments) hemispheres, enhancing the generalizability of the results. One limitation is that all participants were young adults, which restricts the generalizability of the findings to other age groups, such as older adults and children. Finally, in our experiments, we did not include participants with a history of neurological or psychiatric conditions and chronic consumption of psychoactive substances. The findings reported here, especially the ones regarding the metacognitive domain, which were only tested in our data sets, may not generalize to these populations.

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