Integrating explicit reliability for optimal choices: effect of trustworthiness on decisions and metadecisions

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Abstract

In everyday life, decision-makers need to integrate information from various sources which differ in how reliable the provided information is. The present study addressed whether people can optimally use explicit information about the trustworthiness of the information source and whether people know how information sources affect their decisions. In each trial, we presented a sequence of six information sources which indicated a correct colour (red or blue) each with a different level of reliability. For each source, the reliability percentage, i.e., the likelihood that a source provides correct information was explicitly labelled. Participants were asked to decide which colour was more likely to be correct. In the first series of three experiments, we found that participants failed to make use of explicit reliability cues optimally. In particular, participants were less able to use reliably wrong information sources (reliability below 50%) than reliably right information sources (reliability above 50%), even though these two types of information sources were equally informative. In addition, participants failed to ignore the colour displayed by unreliable sources (50% reliability), although these sources gave just random information for a binary decision. In the second series of two experiments, we asked participants, after each choice, to report their subjective feelings of whether they followed or opposed a colour suggested by sources with a specific reliability percentage. We found that the ratings of the participants' influence report tracked the amount of evidence which supported the choice they just made. Further, participants were able to detect their own choice bias guided by unreliable information sources. These findings suggest that human choice behaviour deviates from Bayesian integration. However, people have a good metacognitive monitoring of how their decisions are driven by external stimuli.

Keywords

Evidence accumulation, Bayesian decision theory, metacognition, introspection

Introduction

In today's fast-paced digital world, we are facing an increasing quantity of information coming from various sources ranging from social media and new sources, to governments and private companies, on complex and crucial subjects, such as health, environmental or economic issues. One challenge is the need to integrate information from these sources even it is contradictory and when the sources themselves vary in their reliability. At first sight, providing explicit information about the reliability of each source should help people to weigh appropriately the information they receive. However, empirical evidence on the efficiency of trustworthiness ratings on information usage are mixed. For instance, some studies found that providing 1-to-5 stars rating of news source reduces the tendency to believe and share false information (Celadin et al., 2023; Epstein & Robertson, 2015; Hansen et al., 2014) while other studies found that providing a reliability labels has no effect of on consumption of information from unreliable sources nor on the perception of misinformation (Asslett et al., 2022). These studies suggest that we do not fully understand yet to what extent, and through which cognitive mechanisms people integrate and combine information from sources of heterogeneous reliability when making a decision. Yet, such an understanding appears to be necessary to design efficient information policies.

In order to address this question, one should first understand how subjects encode the reliability of information sources. Bayesian decision theory (BDT) provides a mathematical model of how information reliability should be combined with evidence to make decisions (Berger, 1985; Maloney & Zhang, 2010). The BDT has been shown to accurately capture human behaviour when combining information from different sensory modalities (Ernst & Banks, 2002) or when operating visuomotor control (Kording & Wolpert, 2004; Ota et al., 2020; Tanae et al., 2021; Trommershauser et al., 2005). These studies demonstrate that information is weighted according to the precision of its source, with decisions ultimately being influenced more by accurate than noisy signals. It is therefore reasonable to assume that the reliability of a source is somehow (not necessarily consciously, though) converted into the probability that the information provided by this source is accurate.

Importantly, in most of these studies, experimenters manipulate the quality of the evidence and let participants build their internal representation of those probabilities through feedback. However, humans can also form beliefs about the likelihood of information to be true by being told explicitly how likely it is to tell the truth. Indeed, previous research indicates that people make decisions using explicit probabilistic knowledge, for instance when provided

information about the likelihood of receiving rewards (Kahneman & Tversky, 1984). Interestingly, it has been shown that people often struggle to make optimal choices when reasoning with probabilities. For instance, it was demonstrated that people make choices as if they overestimated the probability of rare events and underestimated the probability of frequent events (Gonzalez & Wu, 1999; Kahneman & Tversky, 1979). This distortion of probabilistic information through a non-linear probability weighting function resembling an “inverted S-shape” has been confirmed in several studies (Tversky & Kahneman, 1992) and is the subject of intense research (Martins, 2006; Ungemach et al., 2009). Results suggest that these distortions are not necessarily stable between tasks (Wu et al., 2009) however, they show, for instance, that estimation of probabilities based on experience can lead to the underestimation of rare events (Hertwig et al., 2004). One explanation for these discrepancies is that distortion could be adapted according to the range of probabilities presented (Zhang & Maloney, 2012; Zhang et al., 2020) leading to specific biases and suboptimalities depending on the context. However, it is less clear whether suboptimal choices arise when probabilities are not about the likelihood of an event occurring but about the reliability of providing correct information. In other words, is explicit probabilistic knowledge about the reliability of the information source subject to specific decision biases?

Crucially, the human cognitive system forms probabilistic beliefs about both the external world and its own functions (Koriat, 2006; Son & Schwartz, 2002). Indeed, recent research in the field of metacognition has shown that people accurately monitor their own cognitive processes (Fleming & Dolan, 2012; Katyal & Fleming, 2024) and detect their errors (Charles et al., 2014; Charles et al., 2013; Charles & Yeung, 2019; Yeung & Summerfield, 2012). Beyond simply tracking whether their choice is correct or not, people actually form probabilistic beliefs about their decisions, computing on the level of evidence supporting the decisions they made and the likelihood of that decision to be correct (Meyniel, 2020; Meyniel & Dehaene, 2017). These judgments of confidence are essential for people to communicate their beliefs (Bang et al., 2014). Indeed, people are able to use other people’s confidence when incorporating advice (Carlebach & Yeung, 2023; Pescetelli et al., 2021; Pescetelli & Yeung, 2021) and when making decisions with another person (Bahrami et al., 2010; Hertz et al., 2017). This research starts to shed light on how people interpret the reliability of the decisions of others when making joint decisions. However, it remains unclear how people use reliability estimates that come from external sources.

More importantly beyond understanding decisions, the question of whether people can accurately monitor how much weight they, in fact, give to different sources of information remains underexplored. In other words, if people are assigning a certain weight to a source, can they produce a clear account of how they do it? Preliminary research suggests that when people must base their choice on a combination of several attributes, they often use quick heuristics to solve problems (Glöckner & Betsch, 2023), but struggle to know the factors that influenced them the most (Cash & Oppenheimer, 2024a, 2024b). People often misattribute the true reasons for their decisions (Celadin et al., 2023; Epstein & Robertson, 2015; Hansen et al., 2014), falling victim to "bias blindness" (Greenwald et al., 1998; Nosek et al., 2005; Pronin, 2007; Pronin et al., 2002). People can even experience an illusory sense of control (Sidarus et al., 2013; Wenke et al., 2010) over decisions that are, in fact, manipulated (Charles & Haggard, 2020; Kummen et al., 2023). However, it remains unclear whether people are aware of how information reliability affects their choices.

In the present study, we have developed a novel paradigm that mimics combining information from sources of variable reliability. In the task, participants see successive samples (red and blue squares) supporting one of two possible responses (red or blue). Each sample is associated with a percentage corresponding to the reliability of the source—the probability that the source is showing correct information about the true underlying colour. Participants must combine the evidence (the colour of the squares) with the reliability score of the source (the percentage) to decide which response it supports. After viewing 6 samples, they decide which response (red or blue) is likely to be correct.

We conceptualised three categories of source reliability based on the percentage. First, reliability scores that are above 50% mean that the source is more likely to give correct information and is therefore *reliably right*. For these sources, Bayesian decision theory allows us to compute the weight it should be given according to its reliability score. Second, a reliability score equal to 50% means that the source is as likely to give correct information as incorrect information. Such a source was categorised as *unreliable*. Importantly, Bayesian decision theory predicts that unreliable sources should be ignored as they are not predictive of the correct response, being as informative as a coin flip. Filtering out unreliable information is likely to be cognitively demanding however (Jiwa et al., 2023; Vidal-Perez et al., 2024) and we hypothesized that it might still bias choice. Indeed, preliminary results in a similar task indicate that the mere presence of unreliable sources decreases choice accuracy and also reduces choice confidence. Finally, reliability scores below 50% mean that the source is more likely to

give incorrect information than correct information, making it *reliably wrong*. Importantly, a reliably wrong source requires participants to reinterpret its prediction as evidence against the content it displayed. BDT also predicts that reliably wrong sources should be treated as equally informative as reliably right sources, as the information they provide allows us to make accurate predictions about the correct response. Yet, counterfactual thinking is known to be cognitively demanding (Van Hoeck et al., 2015). Indeed, previous results suggest that people struggle to use reliably wrong information, its mere presence being associated with a decrease in accuracy and confidence (Jiwa et al., 2023; Vidal-Perez et al., 2024).

The first aim of our study was therefore to investigate how people used these three categories of sources reliability and whether they could assign appropriate weight to the evidence provided by sources based on explicit percentages about reliability. To test this, we developed a computational model of participant choices, hypothesising that participants encode the reliability probabilities of the sources in a distorted way and update their belief with some degree of recency, giving different weights to evidence according to its position in the sequence. In a second series of experiments, we also asked participants to rate, using a visual analogue scale, the extent to which they felt their choice was influenced by a given source of information. Therefore, this design allowed us to compare *objective influence*, the extent to which a choice is influenced by information from a given source, with *subjective influence*, the extent to which participants perceive a given source influences their choice. We show that the weight participants assigned to information is not optimal, with giving too much weight to unreliable information and too little weight to reliably wrong information. Nevertheless, we demonstrate that the subjective feeling of influence was correlated with the actual strength of influence. In particular, participants were able to report being biased by unreliable sources. These findings suggest that human behaviour deviates from optimality but metacognitive monitoring allows to detect those biases.

Results

Task accuracy

In five experiments, participants performed a decision-making task where they had to sample information from different sources of varying reliability to decide between two options. On each trial, the correct colour (red or blue) for that trial was randomly drown from two equally probable possibilities (Figure 1A). To decide which colour was the correct one, participants were shown a sequence of six evidence samples consisting in the opinion of six sources about the correct colour, displayed as red and blue square (Figure 1B). The reliability of the source, i.e. its likelihood to give correct information was shown on top of each square as a percentage. For each information source, the reliabilities of the sources were chosen from three levels with equal probability (50%, 55% and 65% in Experiment 1a; 50%, 45% and 65% in Experiment 1b; 50%, 55% and 35% in Experiment 1c, 50%, 55% or 65% in Experiment 2a; 50%, 45% or 35% in Experiment 2b). The participant's task was to choose a colour that they believed was more likely to be correct after sampling six information sources. Feedback was provided after each choice. In Experiments 2a and 2b, participants were asked additionally to report how *they felt* their choice was influenced by a particular source (for instance, 65% or 35% in Figure 1B), chosen at random (50%, 55% or 65% in Experiment 2a; 50%, 45% or 35% in Experiment 2b). Participants rated the influence on a scale ranging from negative influence (i.e., I responded opposite to the colour the squares indicated) to positive influence (i.e., I responded according to the colour the squares indicated), with no influence presented in the middle.

Importantly, the sources of information were overall equally informative in all experiments. The sources with 55% and 65% reliability were *reliably right*, because these sources displayed a colour that was more likely to be the correct one. The sources with 45% and 35% reliability were *reliably wrong*, because these sources displayed a colour that was more likely to be the incorrect one. Crucially however, a source of 45% reliability is as informative as a 55% reliable source to predict the correct colour, as is a source of 65% reliability compare to a 35% reliability source. The source with 50% reliability was considered *unreliable* however because the colour predicted by this source was equally likely to be correct than wrong. Participants were given careful explanations about these three types of reliability levels to make sure they understood what these reliability levels meant (see Methods).

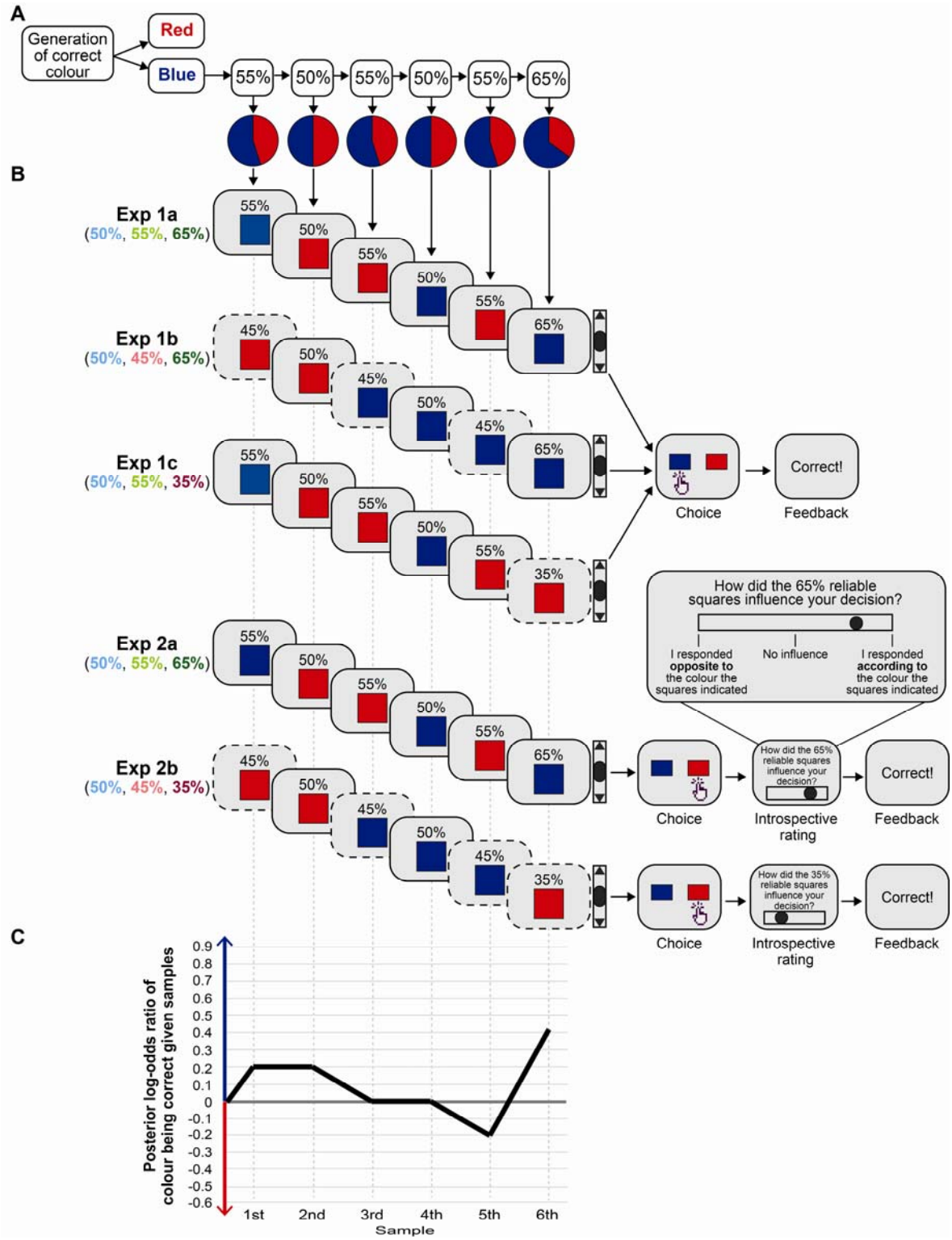

Figure 1. Decision based on information reliability.

(A) Generative process of creating the information sequence. Each information source is generated by choosing a level of information reliability. The colour it displayed is chosen according to the correct colour, with a probability corresponding to its reliability. **(B)** Participants scrolled a webpage to view a sequence of six information sources, each predicting a colour. The reliability of each piece of information was displayed as a percentage value which corresponded to the likelihood that the source would show the true webpage colour. In Experiment 1a and 2a, the reliability percentage varied between 50%, 55% and 65%. In Experiment 1b and 2b, sources of 55% reliability were inverted to 45% reliability. In Experiment 1c and 2c, sources of 65% reliability were inverted to 35% reliability. Sources below 50% reliability predicted the opposite colour but with equivalent informativeness. After viewing the predictions, participants were asked to choose which colour they believed would be the correct colour which had generated the sequence. In Experiment 2, after choosing the colour, participants were additionally asked to rate their subjective sense about the degree to which the information sources of a particular reliability level influenced their choice. Participants used a continuous scale to indicate whether they followed the colour the squares indicated or opposed to the colour the squares indicated. In each trial, one of the three levels of information reliability was chosen at random to ask the subjective feeling of influence at that reliability on their choice. **(C)** The predictions of the colour were accumulated from one sample to another. The posterior log-odds ratio between blue being correct and red being correct given samples can be computed. The ideal decision maker chooses blue once the log-odds ratio at the final sample exceeds 0.

We found participants could perform the task with good accuracy overall (grey circles in Figure 2A), being above chance in all experiments (Exp 1a: mean = 64.0%, 99% confidence interval [CI] = [61.7, 66.4]; Exp 1b: mean = 61.6%, 99%CI = [58.3, 64.9]; Exp 1c: mean = 59.9%, 99%CI = [55.4, 64.4]; Exp 2a: mean = 64.4%, 99%CI = [62.4, 66.4]; Exp 2b: mean = 58.2%, 99%CI = [54.6, 61.9]), without any significant difference in accuracy across experiments the first set of experiment (Exp 1a vs. Exp 1b: t [45] = 1.78, p = 0.16; Exp 1a vs. Exp 1c: t [50] = 2.24, p = 0.06). We found that accuracy was lower however for Experiment 2b, where all the sources of information were reliably wrong compared to when information was reliably right in Experiment 2a (t [62] = 4.43, p < 0.001), indicating that participants were less able to use information appropriately when it was framed as reliably wrong.

Crucially, as the reliability of the sources presented varied randomly from trial to trial, the difficulty of the decision also varied. To estimate trial difficulty, we computed the posterior probability that blue would be the correct response given the sequence of evidence presented using Bayes rule (see Methods & Figure 1c). An optimal Bayesian observer maximising decision accuracy should choose blue if the final posterior probability is superior to 50% and the corresponding posterior log-odds ratio exceeds 0, and red otherwise. As previously stated, a Bayesian optimal observer choice is as influenced by reliably right than reliably wrong sources, but they should ignore information provided by the unreliable (50%) sources.

We compared the participant's choice with the choice predicted by the Bayesian optimal observer. We found participants made optimal choices in 70-80% of the trials (Exp 1a: mean = 80.3%, 99%CI = [76.0, 84.6]; Exp 1b: mean = 74.6%, 99%CI = [68.1, 81.2]; Exp 1c:

mean = 73.0%, 99%CI = [63.7, 82.4], Exp 2a: mean = 84.4%, 99%CI = [80.0, 88.8]; Exp 2b: mean = 69.4.2%, 99%CI = [61.7, 77.2]), showing good performance overall. Crucially, we found participants made less optimal choices when reliably wrong information was present, both in Experiment 1 (Exp 1a vs. Exp 1b: t [45] = 2.28, p = 0.054; Exp 1a vs. Exp 1c: t [50] = 2.15, p = 0.07) and Experiment 2 (Exp 2a vs. Exp 2b: t [62] = 5.04, p < 0.001), confirming reliably wrong information was not used as optimally as reliably right information. The percentage of correct choices by the optimal observer was on average 67.9% (67.4% in Exp 1a; 68.5% in Exp 1b; 68.1% in Exp 1c; 67.5% in Exp 2a; 67.8% in Exp 2b). This means that the participant's efficiency of making correct choices relative to the optimal observer (Juni et al., 2012) was 90.8%. Therefore, participants lost 9.2% of the maximum possible accuracy relative to the optimal observer.

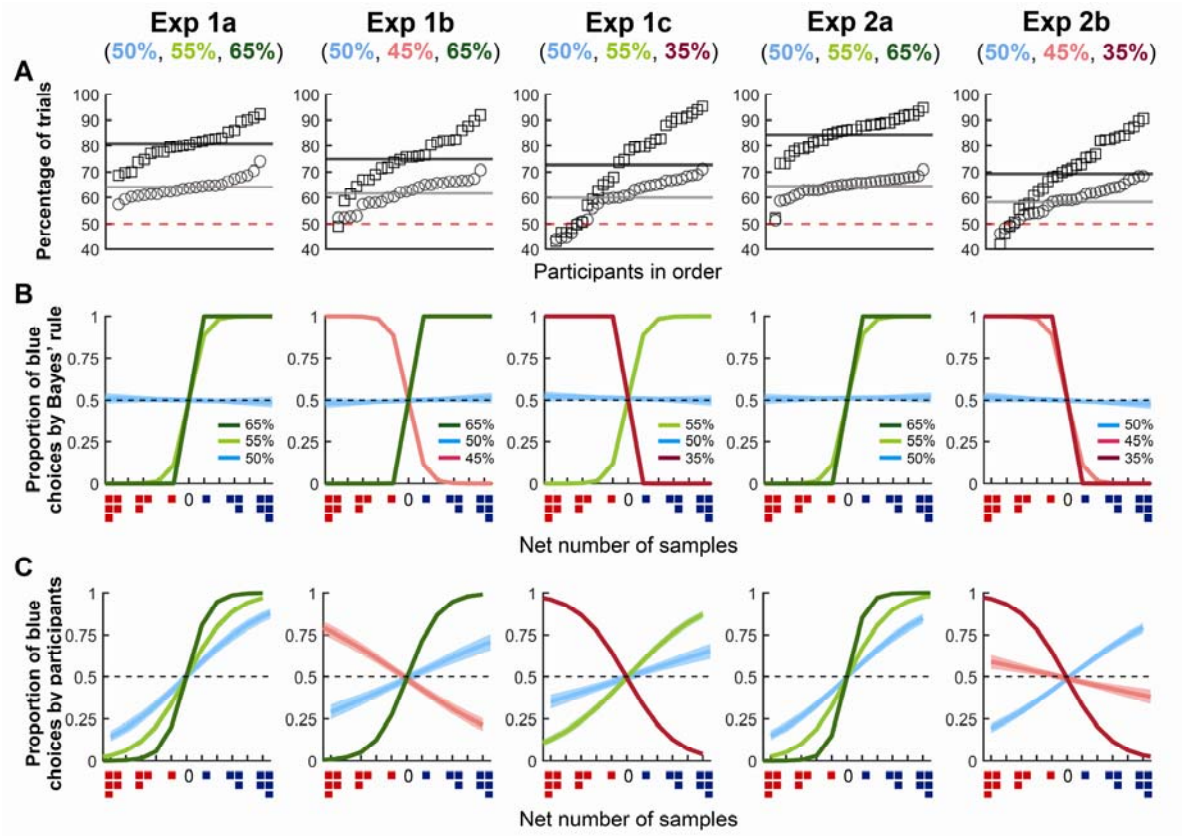

Figure 2. Measuring the influence of information reliability on choice.

(A) Grey circles: Percentage of trials where the participant's choice matched the correct colour. Black squares: Percentage of trials where the participant's choice matched the optimal choice predicted by Bayes' rule. Percentages are ordered from the lowest to the highest performance. Horizontal lines denote the mean across

participants. **(B)** Proportion of choosing the blue option predicted from the optimal choices as a function of the net number of samples for blue or red. Coloured curves denote different levels of information reliability. **(C)** Proportion of choosing the blue option predicted from participants' choice. A positive slope indicates that the proportion of blue choices increases as the net number of blue samples displayed by each level of information reliability increases.

The influence of information on choice is proportional to source reliability

Next, we quantified the extent to which each of the three sources influenced the participant's choices and compared it to the influence predicted by a Bayesian optimal agent. To do so, we computed, for each sequence and for each of source of a given reliability, the difference between the number of red and blue squares it displayed. This can be understood as the amount a source of a given reliability level supports one colour more than the other (see Methods). We used a logistic regression approach to determine the number of samples of a given colour for each reliability level would be predictive of the choice.

As can be guessed intuitively, the proportion of choosing the blue option for an optimal Bayesian observer increased when a given sequence displayed more blue squares of 55% and 65% reliability (Figure 2B: light green curve and dark green curve, respectively). A 65% reliability source had the most impact on choice and led to a step-like increase in the proportion of blue choices, with a net difference of only one source displaying either one of the colours producing a 99.9% change in choosing that colour. Participants also displayed such behaviour, sources with stronger reliability being associated with a steeper regression slope than sources with weaker reliability in Experiment 1a (65% vs. 55%: $z = 16.3$, $p < 0.001$; 55% vs. 50%: $z = 9.1$, $p < 0.001$), in Experiment 1b (65% vs. 45%: $z = 21.8$, $p < 0.001$; 45% vs. 50%: $z = 2.9$, $p < 0.05$) and in Experiment 1c (35% vs. 55%: $z = 9.6$, $p < 0.001$; 55% vs. 50%: $z = 10.7$, $p < 0.001$). This result was replicated in Experiment 2a (65% vs. 55%: $z = 22.7$, $p < 0.001$; 55% vs. 50%: $z = 11.5$, $p < 0.001$) and in Experiment 2b (35% vs. 45%: $z = 23.5$, $p < 0.001$; 45% vs. 50%: $z = 8.3$, $p < 0.001$), confirming that the likelihood of participants to choose one colour gradually increased when the source reliability became stronger.

Choice behaviour is modulated by the presence of reliably wrong source

As predicted, the proportion of blue choices was reversed for the reliably wrong sources, the optimal choice being now to select the opposite colour to the prediction of the 45% or 35% reliability sources (pink curve or red curve respectively in Figure 2B). Crucially, for those sources, sign of the slope of the logistic regression was reversed compared to reliably

right ones, without changing its absolute value. This captures the fact that according to Bayes' rule, reliably wrong information is as informative as reliably right information.

Turning to the behaviour of participants, however, different results were observed. Comparing the use of reliably wrong and reliably right information, the slope of logistic regression was shallower for reliably wrong sources than for reliably right ones, both in Experiment 1 and Experiment 2. Regression coefficients of the 55% reliability source on choice behaviour were significantly greater in absolute value than negative coefficients of the 45% reliability source (Exp 1a: β = 0.68, 99%CI = [0.60, 0.76] vs Exp 1b: β = -0.25, 99%CI = [-0.32, -0.19], z = 12.9, p < 0.001; Exp 1a vs Exp 1c: β = 0.38, 99%CI = [0.33, 0.43], z = 9.3, p < 0.001; Exp 2a: β = 0.72, 99% CI = [0.65, 0.79] vs Exp 2b: β = -0.08, 99% CI = [-0.13, -0.03], z = 21.7, p < 0.001). Similarly, positive regression coefficients of the 65% reliability source were greater in absolute value than negative regression coefficients of the 35% reliability source (Exp 1a: β = 1.40, 99%CI = [1.29, 1.50] vs Exp 1c: β = -0.63, 99%CI = [-0.69, -0.57], Exp 1a vs. Exp 1c: z = 19.3, p < 0.001; Exp 1b: β = 0.95, 99%CI = [0.88, 1.03] vs Exp 1c, z = 10.3, p < 0.001; Exp 2a: β = 1.73, 99%CI = [1.62, 1.84] vs Exp 2b: β = -0.66, 99%CI = [-0.71, -0.60], z = 25.9, p < 0.001). Therefore, the presence of reliably wrong information reduced the sensitivity to information. In other words, although reliably right information is as informative as reliably wrong information, human participants failed to optimally use information that was reliably saying the opposite of the truth.

The presence of unreliable information sources biases choice behaviour

According to the Bayesian optimal observer, the colour shown by a 50% reliable source (i.e., unreliable information) should not impact the choice because it is not predictive of the correct response. Indeed, the proportion of blue choices by the simulated optimal observer did not increase with the net number of samples of a given colour displayed by 50% reliability (Figure 2B, blue line). In contrast to this prediction, the net number of 50% reliable samples impacted the choice of participants in both Experiment 1 (Exp 1a: β = 0.36, 99%CI = [0.29, 0.43]; Exp 1b: β = 0.17, 99%CI = [0.11, 0.23]; Exp 1c: β = 0.12, 99%CI = [0.07, 0.17]) and Experiment 2 (Exp 2a: β = 0.34, 99% CI = [0.28, 0.41]; Exp 2b: β = 0.28, 99% CI = [0.23, 0.33]). That is, participants chose the blue option more frequently when one or more unreliable sources (50% reliability) were blue. These results demonstrate that, even when unreliable information is explicitly labelled as such, people fail to ignore unreliable cues by demonstrating a positive bias by the colour that these cues display.

A computational account for choice behaviour

This first set of analyses suggest a deviation from optimality when using sources' reliability. To shed light on the origin of these suboptimalities in the information integration process, we turned to computational modelling. We considered two potential factors leading to reliability misuse: 1) the distortion in how the reliability score is encoded (i.e. a 50% unreliable square is actually treated as slightly reliable 52%) and 2) how the information is lost through decay during sequential sampling (i.e., the information presented last is overweighted compared to earlier information). Figure 3 illustrates how these two sources of errors were modelled and use to predict choice. When presented a colour square of a given reliability, the computational model first encodes the source reliability in a distorted way, transforming the probability through a non-linear probability distortion function (Gonzalez & Wu, 1999). This transformation is mathematically equivalent to applying a biased linear transformation to the log-odds space of the probability (Zhang & Maloney, 2012; Zhang et al., 2020). Then, the computational model assumed that a different weight is given to each sample of the sequence depending on its position. Finally, the model computes the posterior log-odds of each colour by summing the log-odds of the prior evidence with the log-odds of the new evidence for the colour the source displayed.

We built four models including both distorted encoding of the reliability and sequential weighting gradually to determine which of these two sources of errors predicted the choice best (see Methods). The first model was included no distortion in the encoding of information reliability and no memory loss, mimicking the behaviour of an optimal Bayesian observer model (BDT). The second model corresponded to the optimal observer with no distortion in the encoding of the reliability but with sequential weights mimicking the effect of memory decay. The third model corresponded to an observer that would encode the reliability scores with a certain degree of distortion but without memory loss. The fourth model included the two sources of suboptimality: sequential weights and distortion in the encoding of reliability. We used a hierarchical Bayesian model fit procedure to model trial-wise choice behaviour, confirming the recovery of group-level parameters and individual-level parameters was robust (Supplementary Figure 1 & Supplementary Figure 2).

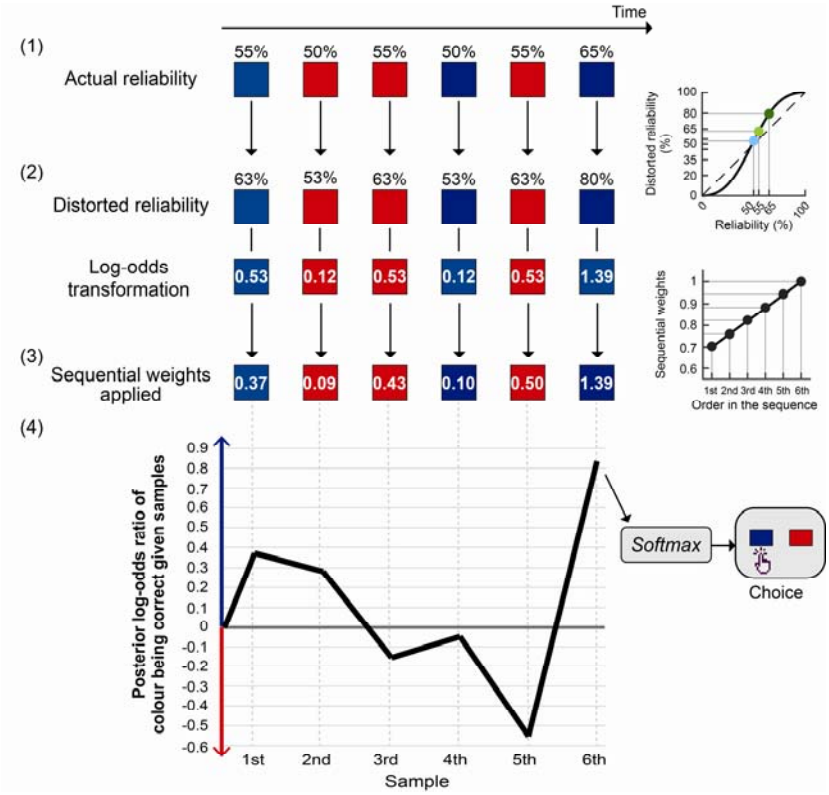

Figure 3. A schematic illustration of computational model.

(1) In each trial, a sequence of six information samples coming from six sources was presented. Each source displayed the prediction of the colour (blue or red) with its reliability score labelled by a percentage above it. (2) The computational model of the choice proposes that the decision maker distorts the reliability percentage via non-linear probability distortion function (right panel) (Gonzalez & Wu, 1999). This is equivalent to a biased linear transformation of log-odds of the objective reliability percentage (Zhang & Maloney, 2012; Zhang et al., 2020). (3) The subjective log-odds is further distorted by a memory leak. Each source of information is weighted depending on the order in which the information source was presented (right panel). (4) Evidence for each colour is accumulated by adding the subjective log-odds of the reliability from one sample to another. After the final sample is presented, a softmax decision rule is applied to the subjective posterior log-odds ratio to determine a choice. The decision maker becomes more likely to choose blue as the log-odds ratio increases.

In all experiments, the BDT model performed the worst to fit the data (Figure 4A). On the opposite, the full model including both sequential weight and distortion of reliability outperformed the other three models. Additionally, the reliability distortion model was significantly better than the sequential weights model to predict choice, suggesting that participants' choices were better explained by a distorted perception of information reliability than by sequential weights.

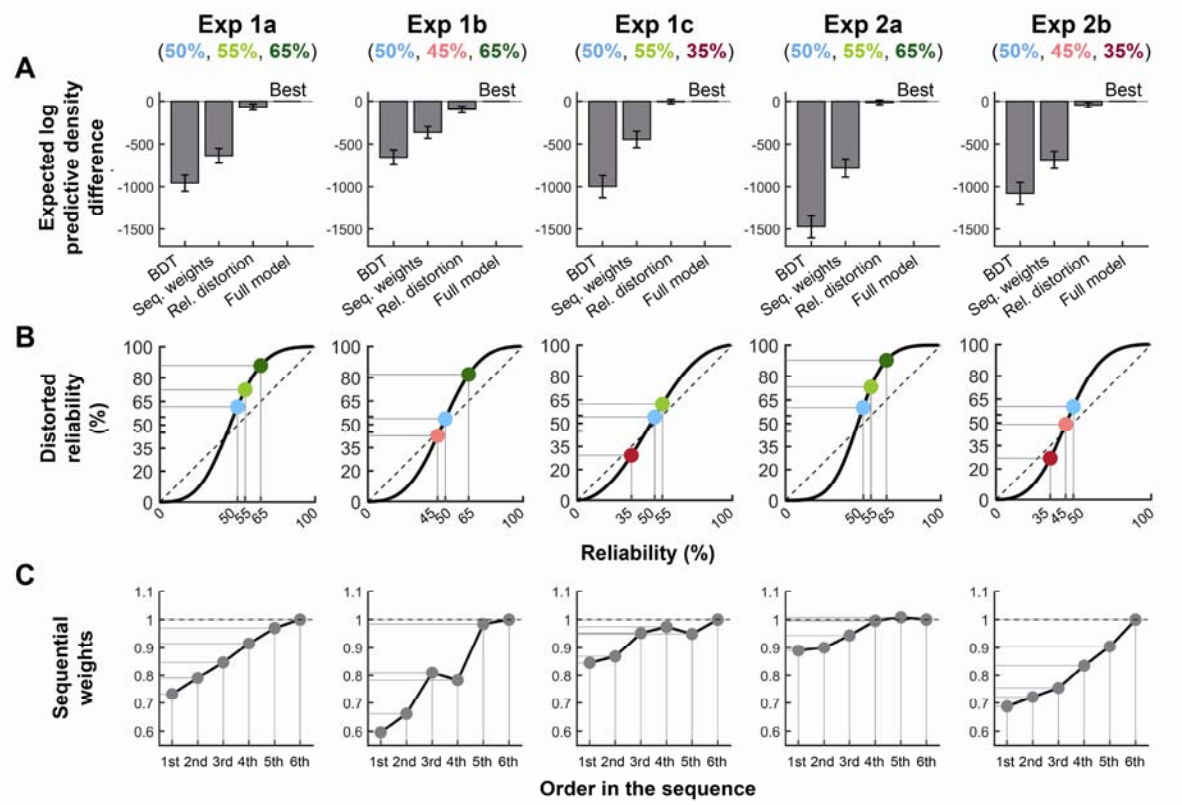

Figure 4. Results of computational analysis.

(A) Expected log pointwise predictive density denotes the out-of-sample predictive accuracy of the model explaining the choice data. The lower the value, the worse the model. The full model which had distortion in reliability and sequential weights on information sources accounted for the data best. **(B)** Distorted reliability percentage recovered from the full model. **(C)** Sequential weights recovered from the full model.

From the full model, we could retrieve, for each information reliability level, the fitted percentages corresponding to the estimates of reliability across participants (Figure 4B, coloured circles). The model predicted that the 50% reliability squares were treated as having above chance reliability in both the first three experiments (61.4% in Exp 1a; 53.7% in Exp 1b; 54.0% in Exp 1c) and the second two experiments (60.1% in Exp 2a; 60.2% in Exp 2b). This pattern of the result is consistent with the previous descriptive result of the positive bias by the colour displayed by the unreliable (50%) information sources. Further, the participants treated the reliably right and reliably wrong sources as more reliable than they actually were, the sources of 55% reliability (72.4% in Exp 1a; 62.3% in Exp 1b; 73.2% in Exp 2a) and 65% reliability (88.0% in Exp 1a; 82.0% in Exp 1b; 90.4% in Exp 2a) being treated as *more* correct than they were and the 45% reliability (42.7% in Exp 1b) and 35% reliability (29.2% in Exp 1c;

26.8% in Exp 2b) as being more wrong than they were. Regarding the sequential weights, we found that participants gave less weight information sources presented earlier in a sequence, resembling memory loss or underweighting of prior information. In particular, weights placed on the first source were, on average, 27.5% smaller than the last source in Experiment 1 and 21.1% smaller in Experiment 2.

A Bayesian hierarchical model estimates a full posterior sample of the model parameter and thus allows us to compare a difference in parameter values between experiments. The full model included two group-level parameters which define a shape of reliability distortion (i.e., the parameter for the sensitivity to information and the parameter for the presentation bias) as well as group-level parameters for memory leak on the first five samples in a sequence (see Methods). We retrieved the posterior distributions of these seven group-level parameters for each experiment from the fit of the full model (Supplementary Figure 3). We performed a pairwise comparison of the parameters between experiments to test whether the presence of reliably wrong information in Experiment 1 affected the reliability distortion and memory leak. We found that the parameter capturing the bias by unreliable sources was significantly smaller when a reliably wrong source was present (Experiment 1 b&c) compared to when all sources were reliably right (Exp 1a: Mean parameter value = 0.47, 99%CI = [0.22, 0. 73]; Exp 1b: Mean = 0.15, 99%CI = [-0.01, 0.32]; Exp 1c: Mean = 0.16, 99%CI = [0.06, 0.27]; Exp 1a vs. Exp 1b: p = 0.008; Exp 1a vs. Exp 1c: p = 0.005). This result indicates that the positive bias by unreliable sources was mitigated by the presence of reliably wrong information sources. No significant difference between experiments was found for the other six parameters. We repeated the same analysis for Experiment 2 to test whether framing all evidence as reliably wrong affected the reliability distortion and memory leak. Although we did not find differences in the two parameters for reliability distortion, we found that the parameter values for five sequential weights were significantly smaller in Experiment 2b than in Experiment 2a (ps < 0.037; see Supplementary Figure 3), suggesting that memory leak was increased when the sources of information were reliably wrong.

To summarise, a computational analysis suggests that people place subjective weights on the reliability of sources, even when the reliability scores were given explicitly. Participants tend to consider unreliable sources to be reliably right but this effect is mitigated when reliably wrong sources of information are present. Moreover, participants overweight the last information they received compared to the first piece of information.

How do people feel the influence of information reliability on their choices?

In Experiment 2, we asked participants to report how much their decisions were influenced by the evidence provided by each reliability source. We reasoned that if participants were aware of the influence of information reliability on their choice, their subjective report would increase with the reliability of the source considered for the introspective report, as well as with the net number of congruent samples of that source supporting the choice. Therefore, we built a regression model predicting the trial-by-trial ratings of influence using 1) the reliability value of the source chosen for the introspective report and 2) the net number of samples of that reliability level congruent with the choice (see Methods).

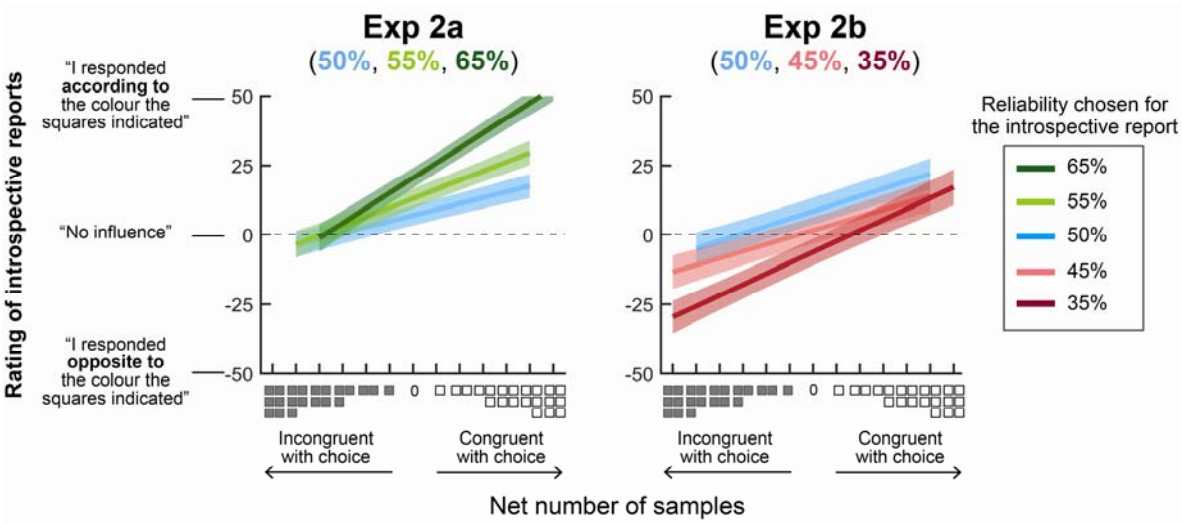

Figure 5. Measuring the subjective feeling of the influence of information reliability on choice. Rating of introspective reports as a function of the net number of samples for congruent or incongruent with the colour the participant chose and of the reliability level that was chosen for the introspective report. A positive slope indicates that the subjective feeling of following the colour increases as the net number of congruent samples displayed by a particular level of information reliability increases.

The ratings of influence increased with the net number of samples congruent with the choice, as shown by the positive regression slope for the 65% (β = 5.40, 99% CI = [4.76, 6.02]) and 55% reliable sources (β = 3.30, 99% CI = [2.73, 3.88]). Similarly, in Experiment 2b, we also observed a positive slope for the 35% (β = 3.90, 99% CI = [3.26, 4.54]) and 45% reliable sources (β = 2.50, 99% CI = [1.87, 3.12]). These results suggest that the participant's subjective reports accurately tracked the amount of evidence provided by the source of

information chosen for the introspective report. Note that the ratings of influence were not affected by the information sources that were not chosen for the introspective report (e.g., the net number of 55% or 65% sources when introspecting the influence of 50% reliability, see Supplementary Figure 4).

Next, we examined whether increased source reliability was also associated with a stronger sense of being influenced by the source. We tested this idea by comparing the values of regression coefficients between the reliability levels, within each experiment. We found that a source with stronger reliability had a steeper regression slope than a source with weaker reliability in Experiment 2a (65% vs. 55%: $z = 7.15$, $p < 0.001$; 55% vs. 50%: $z = 4.6$, $p < 0.001$) and in Experiment 2b (35% vs. 45%: $z = 4.7$, $p < 0.001$; 35% vs. 50%: $z = 4.1$, $p < 0.001$). No difference in the slopes between the 45% reliability and the 50% reliability was observed however ($z = 0.7$, $p = 0.99$).

We reasoned that if participants remained unaware of the influence of unreliable information on choice (Figure 2C), the ratings for unreliable (50%) information would be independent of the net number of unreliable samples congruent with the choice. In contrast to this prediction, the ratings of influence for the 50% reliable sources increased with the net number of samples congruent with the choice, as reflected by significant positive slope when the 50% reliability was chosen for the introspective report (Exp 2a: $\beta = 2.11$, 99% CI = [1.58, 2.64]; Exp 2b: $\beta = 2.70$, 99% CI = [2.09, 3.31]). This result suggests that participants could track that unreliable evidence biased their choice and to which extent. Taken together with the results of choice behaviour, our findings suggest that participants adjusted their subjective feelings of influence reflecting on the degree to which their choice was actually influenced by the source of information reliability.

Finally, we explored whether across individuals, the introspective reports reflected how much weight they assigned to information at each reliability level. To do so, we recovered from the best-fitting computational model the distorted reliability score that individuals assigned to each of the three levels of information reliability (Figure 4). The distorted reliability score is a proxy of the extent to which the participant gave weight to the information provided by that source, thereby quantifying the *objective measure of the influence* of that source on behaviour. On the other hand, we also computed the slope of the linear regression in Figure 5 for reliability source and each participant. This slope provides a measure of how sensitive the participants were to the amount of evidence displayed by a particular source reliability when reporting its influence on choice, thereby quantifying the *subjective sense of the influence* of each given

source. For each participant, we correlated the distorted reliability score with the regression slope of subjective influence.

We expected a quadratic relationship between the objective and the subjective measure of influence. This is because, if an individual was aware of the influence of a source on choice, the regression slope of subjective influence should be positive and maximal for sources that are perceived as highly wrong or highly correct. Only for a source with a perceived reliability of 50%, the slope should be equal to 0. Figure 6 illustrates this relation for each reliability level across participants. We fitted both a quadratic model ($y = b_1 * x^2 + b_0$) and a constant model ($y = b_0$) to the data points. We found that in Experiment 2a, the quadratic fit was significantly better than the constant model for the 65% reliable source ($F = 8.27$, $p < 0.01$) and the 55% reliability source ($F = 6.00$, $p < 0.05$) but not for the 50% reliability source ($F = 0.95$, $p = 0.34$). In Experiment 2b, we found a better fit by the quadratic model for the 35% reliability source ($F = 8.68$, $p < 0.01$) and the 50% reliability source ($F = 5.06$, $p < 0.05$) but not for the 45% reliability source ($F = 0.27$, $p = 0.61$). Taken together, these results demonstrate the awareness of the influence of information at the individual level: those who assign a strong decision weight to a source of information are also able to report a stronger sense of being influenced by that source of information, than those who assign a weak decision weight. Our findings (Figure 5 & Figure 6) provide substantial evidence that people are aware of the degree to which particular information sources influence their behaviour.

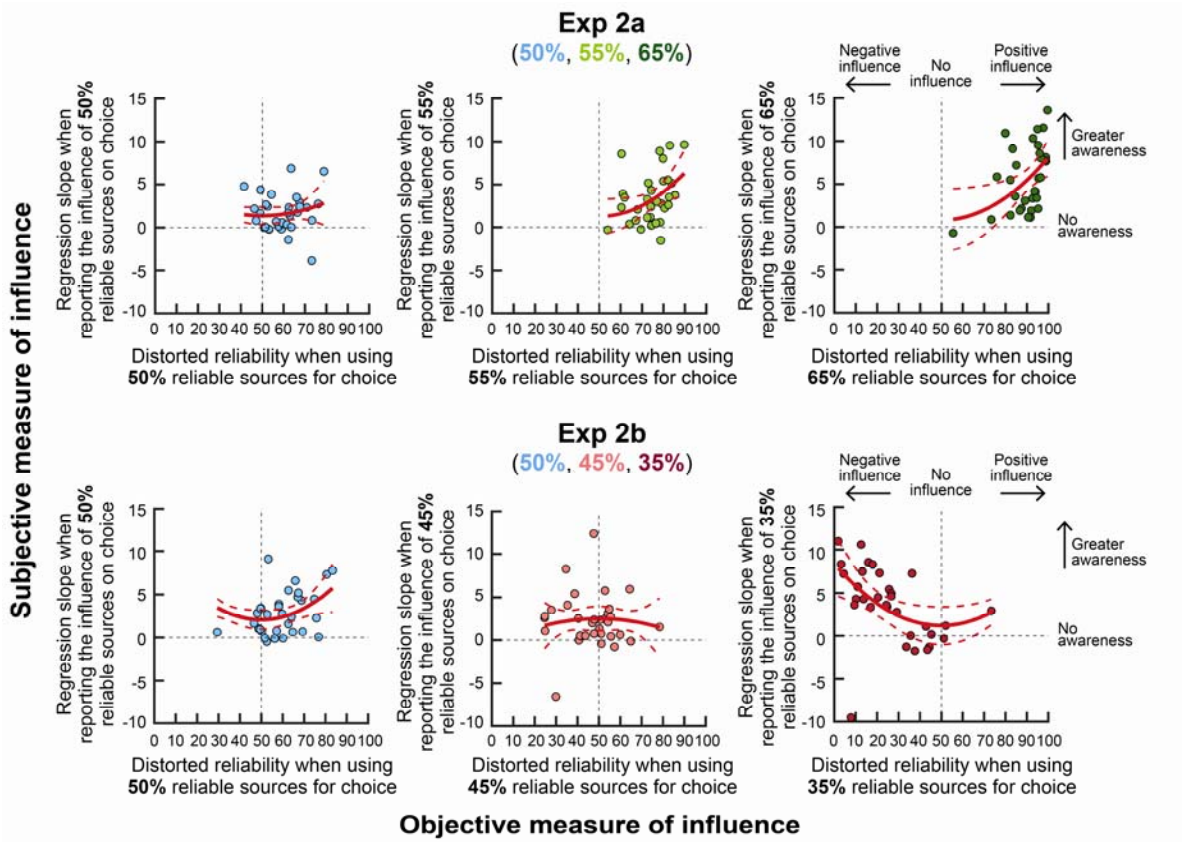

Figure 6. Correlation between the subjective feeling of the influence and the actual strength of the influence.

Across participants, the individual's sensitivity (i.e., the slope of regression) to report the influence of a particular level of information reliability on their choice is plotted against the same individual's distorted percentage for that reliability. The distorted reliability percentage provides a proxy of the weight the individual assigns to a particular level of information reliability when making a choice, and therefore tells the actual strength of the influence on choice. We expected a quadratic relationship between these two measures (see text). In each panel, a solid red curve indicates the quadratic model best fitted to the data points and dashed red curves indicate 95% confidence intervals.

Discussion

In this study, we developed a novel paradigm investigating how people use explicit probabilistic knowledge about the reliability of a source of information when making decisions. Participants saw successive pieces of evidence coming from different sources supporting one

of two possible responses (red or blue). Each sample was associated with a percentage corresponding to the reliability of the source of the information i.e. the probability that the source would show information congruent with the correct color for that trial. Participants had to combine the evidence (the colour of the squares) with its reliability index (the percentage) to decide which response it supported. After viewing 6 samples, participants had to decide which of the two colours they thought was more likely to be correct. In each experiment, participants were presented with reliably right sources of information that were predictive of the correct colour, or reliably wrong sources of information that would show reliably the incorrect colour (experiment 1b-c, experiment 2b). Crucially, they were also presented with unreliable sources of information that were as likely to show correct as incorrect information (50% reliability).

We used a computational modelling approach to determine how participants used the reliability information, testing whether their choice reflected a distorted representation of the reliability of the sources and whether they gave different weights to each sample in the sequence according to their position. Experiment 1 revealed that participants did not use explicit reliability optimally, overestimating the reliability of the unreliable and reliably right sources. Participants also struggled to use reliably wrong sources of information, despite these being in theory equally as informative for the Bayesian optimal observer as reliably right sources. We also found that participants failed to ignore the information provided by the unreliable sources, and instead tended to act in accordance with the response these sources supported. In a second series of experiments, we probed whether participants were aware of these influences on their choice, by asking them to report how a given source influenced their choice. Overall, the participants reported a stronger sense of influence when the reliability of the source increased and when the evidence shown was congruent with the choice. Crucially, participants were also aware that they were positively biased by the unreliable information, speaking in favour of participants' metacognitive ability to monitor their use of explicit reliability.

The question of how humans and other animals estimate and use information about environmental uncertainty has been the subject of intense research (Ma & Jazayeri, 2014; Maloney & Mamassian, 2009). Previous studies on this question have explored how people learn to use information from noisy sensory cues, forming implicit estimations of the reliability of different sources of information to maximize reward (Ma, 2023; Maloney & Zhang, 2010). Crucially, this research has revealed how people form beliefs about source precision through perceptual experience. Importantly, only very few studies have explored how people use explicit probabilistic information about the reliability of sources (Carlebach & Yeung, 2023;

Pescetelli et al., 2021; Pescetelli & Yeung, 2021). Research in social and applied psychology has also started investigating how people form explicit beliefs about source reliability based on their prior beliefs and novel information, looking for instance at the effect of debunking (Radkani et al., 2024; Swire-Thompson et al., 2021). Similarly, research in applied psychology has started to look at how people use reviews and ratings to form opinions on products or companies (Hoffart et al., 2019; Oktar & Lombrozo, 2025). Nevertheless, we lack both empirical evidence and theoretical frameworks for understanding how people use explicit probabilistic knowledge about the reliability of the information they sample to make decisions.

Research in behavioural economics provides the beginning of an answer to this question, revealing clear limitations in making optimal inferences when reasoning with probabilities. It has been established that the perception of the likelihood of events is distorted (Gonzalez & Wu, 1999; Tversky & Kahneman, 1992). The probability of rare events is typically overestimated while frequent events are underestimated. This was demonstrated for decisions under risk where participants are asked to choose between two lotteries where information about the probability of winning and potential rewards is explicitly described (Hertwig et al., 2018). In that situation, it is possible to infer, using the choice patterns of participants, the odds of winning they seem to be basing their choice on. To account for these results, it has been proposed that probabilities undergo a non-linear weighting function resembling an “inverted S-shaped” explaining the overweighting of rare events compared to frequent events (Hertwig et al., 2004; Tversky & Kahneman, 1992; Zhang et al., 2020). In the present paper, we adopted a similar approach to estimate how participants might have distorted the explicit reliability percentages, based on their patterns of choices. We indeed found that participants behaved as if they underestimated small reliability percentages and overestimated medium-to-large reliability percentages, resembling an “S-shaped” function. This suggests that a pattern of probability distortion might extend from distorting the likelihood of an event to distorting the likelihood of information being correct. Indeed we observed that participants particularly overestimated the reliability of the most reliable sources presented. This is in broad agreement with the idea that these distortions happen due to the normalization of the probabilities according to the range of probabilities presented (Zhang et al., 2020). Zhang et al (2020) proposed that when reasoning with probabilistic information, people first transform the probability to log odds so that they can be combined by addition or subtraction rather than multiplication. Then crucially, the log odd values are normalized according to the range of values occurring in the task. This mechanism can explain how the distortion function would

vary across contexts, depending on the range of reliability presented. Further research will be needed to confirm whether this process explains the difference in distortion we observed, by varying systematically the range of reliabilities presented.

Beyond distorting reliabilities, our findings revealed three other types of suboptimal behaviour in participants' decision processes. First, participants were less able to use reliably wrong sources than reliably right sources. This may be due to an increase in cognitive load when processing information provided by reliably wrong information. Indeed, we observed that memory decay in the evidence accumulation process increased when reliably wrong information was present in experiment 2b: participants lost the information presented by the first sample by about 30%. Indeed, participants were required to reinterpret the suggestions by reliably wrong sources as evidence in favour of the opposite colour. Counterfactual thinking is known to engage working memory and affect decision-making (Van Hoeck et al., 2015). Second, participants' choices were biased by the colour suggested by the unreliable information sources. Furthermore, as the number of unreliable samples displaying a colour increased, participants became even more likely to choose the colour suggested by the unreliable sources. This effect was captured by our computational model, showing that participants assigned a probability slightly higher than 50% to unreliable sources, in the range of 53.7% to 61.5%. This was true even though participants were explicitly informed that 50% reliability squares were uninformative, as reliable as a coin flip, and instructed to ignore them. However, the presence of one reliably wrong source in experiments 1b and 1c reduced such a bias. How can we explain that participants were biased by unreliable sources? One interpretation of this finding is that participants tended to be biased by the overall colour present in the sequence, independently of the reliability of the squares. Indeed, it has been shown that repeated exposures to a stimulus enhances preference for that stimulus (Zajonc, 1968, 2001), a phenomenon called "the mere exposure effect". In that context, bias can result from exposure to the colour, similar to a global priming effect by the dominant colour of the sequence. Such interpretation would also explain why an increasing number of unreliable samples biased the choice more. An alternative interpretation is that participants did not actually believe the instruction that unreliable information was truly uninformative for the choice. Indeed, it has been proposed in theoretical work on communication that people assume that communication is cooperative in nature and that the evidence a source provides is by definition informative and as truthful as possible (Grice, 1991). This concept, captured in Grice's maxims could explain why participants fail to conceive the existence of a random source of information,

especially in a context where most sources are reliable. Finally, another possible interpretation of this finding is that participants correctly understood that the information provided by the 50% squares was unreliable and random, but used it the same way people flip a coin when they are unsure of how to decide between two options. Indeed, for many sequences presented, the evidence in favour of both options could be ambiguous, one response being favoured only marginally over the other. In this context of uncertain, it is then possible participants relied on unreliable information to break the tie and choose a response based on the random evidence it displayed.

The results of experiment 2 showed that participants were aware that their response was biased by unreliable information. Indeed, when asked to report the influence of the squares of 50% reliability on their choice, participants confirmed that their decision was positively influenced by their colour. Crucially, participants did not simply report a constant influence but accurately reported increased influence when the number of unreliable sources favouring their choice increased. Taken together, these results suggest that participants were aware of being biased by explicit cues of 50% reliability, confirming participants had some degree of metacognitive access to the factors influencing their choice. One may wonder why participants still followed the colour suggestions from unreliable sources, despite that they were aware of such a positive bias. One possibility is that this finding reflects a form of metacognitive knowledge rather than metacognitive control. It has been suggested that the metacognitive processes rely on a map between monitoring one's own behavioural performance and control of behaviour (Koriat, 2006; Son & Schwartz, 2002). However, people use their metacognitive knowledge to regulate their behaviour when the use of metacognitive control is pronounced (Boldt & Gilbert, 2022; Risko & Gilbert, 2016). Another possibility is that, as suggested above, participants knowingly used the 50% reliable squares to break the tie between options when reliable information about the correct response was sparse. This would be consistent with the increased report of influence when more unreliable squares were present. Most studies of metacognition have focussed on how participants form beliefs about their confidence in their choice in perceptual, memory or motor tasks (Fleming, 2024). A standard approach to measure the accuracy of confidence is to compare *subjective* confidence judgements with the accuracy of *objective* behavioural performance, assuming that high confidence is coupled with an accurate operation of a given task (Fleming & Lau, 2014). In the present study, we developed a similar approach, asking participants the extent to which they felt influenced by a given source of information and comparing this *subjective* sense of influence to an *objective* measure of the

influence of that source on choice. By doing so, it allowed us to provide a quantitative measure of the metacognitive sensitivity in detecting influence in choice. We first confirmed that the strength of sensory cue (in our case, three levels of source reliability) had an increased correlation with both the objective performance of participant's choice (**Error! Reference source not found.**C) and the subjective report of influence (Figure 5). Across participants, we correlated the individual's objective influence of information source on choice with the same individual's subjective sense of influence (Figure 6). Indeed we found a significant relationship between them: those who were strongly influenced by sources of a particular level of reliability also had a stronger sense of being influenced, compared to those who were less influenced. Taken together, these findings suggest that people have a good metacognitive ability to detect the influence of choice reflecting on how their decisions are made.

Importantly, however, subjective reports of influence were not predicted by a more comprehensive measure of influence encompassing the relative weight of a piece of information on choice. Formally, the influence of a piece of evidence on choice can be retrieved by imagining what would have been the behaviour if one had not observed that piece of evidence. In other words, it consists of computing the likelihood of having made the same choice if that piece of evidence was absent and comparing it to the likelihood of making the choice when that piece of information was present using counterfactual thinking to infer influence. These findings seem in contradiction with some social psychological studies showing that people perform poorly when attempting to detect their own biases or reasons for choice (Epstein & Robertson, 2015; Greenwald et al., 1998; Pailhes & Kuhn, 2020; Sidarus et al., 2013). For instance, people are unaware that their behaviour is manipulated by search engine rankings (Epstein & Robertson, 2015) or person's speech and gestures (Pailhes & Kuhn, 2020, 2021). People also tend to evaluate themselves as less subject to various biases and more objective than others (Armor, 1999; Ehrlinger et al., 2005; Hansen et al., 2014; Pronin et al., 2002; Schwalbe et al., 2020). Indeed, our other research has revealed that people suffer from metacognitive blind spots when trying to understand the reasons for their choice, mistaking autonomy for acting contrarian (Kummen et al., 2023). Our design is, of course, different from the design of these studies and these differences might explain the distinct pattern of results here. While the previous studies use cues or manipulations which implicitly guide action choices (Epstein & Robertson, 2015; Greenwald et al., 1998; Pailhes & Kuhn, 2020; Sidarus et al., 2013), our task presented explicit and descriptive cues of source reliability. This difference seems important to raise a conscious awareness about drivers of actions.

In everyday life, explicit, descriptive information about the trustworthiness of information is often available. For instance, online shopping services such as Amazon provide a star rating review indicating customers' global agreement of how good products are (Hoffart et al., 2019; Oktar & Lombrozo, 2025). In social networking services, misleading posts and fake facts are easily disseminated (Vosoughi et al., 2018), which leads people to form false beliefs (Fazio et al., 2013; Rapp, 2008; Rapp & Salovich, 2018). Social networking services add fact-checking flags in the hope that flags could alert people to fake news (Andersen & Søe, 2019; Gaozhao, 2020). Our experimental work implies that people still overly trust or may distrust information, even when such explicit information about trustworthiness is available to them. Indeed, drivers of forming false beliefs include neglecting source cues (Ecker et al., 2022). For example, a logo banner specifying the publisher for online news items has been found not to decrease belief in fake news or increase belief in factual news (Dias et al., 2020). Therefore, a more sophisticated approach such as prebunking or debunking would be important to prevent such cognitive failures (Ecker et al., 2022).

Methods

Participants

Ninety-four participants were recruited on the online platform Prolific (https://www.prolific.co/), to participate in three decision-making experiments: experiment 1a (20 female, 8 male, 2 other, Mean age = 27.2, SD = 4.9), experiment 1b (18 female, 12 male, 0 other, Mean age = 24.6, SD = 5.2), experiment 1c (24 female, 9 male, 1 other, Mean age = 30.0, SD = 4.6). We recruited 64 participants for our two metacognitive experiments: experiment 2a (22 female, 9 male, 1 other, Mean age = 26.3, SD = 5.2) and experiment 2b (25 female, 6 male, 1 other, Mean age = 28.6, SD = 4.7). Recruitment was restricted to the United Kingdom. All participants were fluent English speakers and had no history of neurological disorders. Participants received a basic payment of £8 for their participation in a 60-minute experiment. Participants who took less than half the expected time to complete the task (i.e., 30 mins) were excluded from the analysis as they were considered not to have engaged with the instructions properly. This exclusion left final samples of 23 participants for experiment 1a, 24 for experiment 1b and 29 for experiment 1c. No participants were excluded from the analysis in experiments 2. All participants gave informed consent. The procedures were approved by the Research Ethics Committee of University College London (ID ICN-PH-PWB-22-11-18A).

Experimental design

Experiment 1

Apparatus. The online task was programmed using jsPsych (de Leeuw, 2015) and the experiment was hosted on the online research platform Gorilla (https://gorilla.sc/) (Anwyl-Irvine et al., 2020).

Stimuli and task. On each trial, a colour (blue or red) was chosen at random as the correct colour for that trial (Figure 1A). The participants' task was to guess which colour was more likely to be correct. To help participants guess, we generated six *information sources* which predicted the correct colour. Each piece of evidence provided by the sources was a red or blue square (200x200 pixels) accompanied with a percentage that indicated the likelihood of the source to give accurate information about the correct colour. That is, each coloured square was associated with an explicit cue indicating the reliability score of the source (i.e., reliability of the evidence). Reliability scores varied between three levels in each experiment: 50%, 55% and 65% in Experiment 1a; 50%, 45% and 65% in Experiment 1b; 50%, 55% and 35% in

Experiment 1c. To generate the stimulus sequence, the reliability score of the source was fist chosen at random among the three levels (Figure 1A). Then the colour of the square was drawn from a Bernoulli distribution with a probability of choosing the correct colour equal to the reliability score. For instance, if the correct colour was blue and a 65% reliable source had been chosen to be displayed, the colour of the square was generated at random, with a 65% chance of it being blue and a 35% of it being red. The reliability score (in this case 65%) was labelled above the centre of the square. Therefore, each information source explicitly signalled the probability that the displayed colour is the correct one (i.e., the likelihood of the correct colour). To generate the stimuli sequence, this process was repeated six times, generating six information samples shown to the participant (Figure 1A). As a consequence of the stochastic generative process, the strength of evidence supporting a correct colour varied across trials. Crucially, it could be that the information would by chance support the incorrect response, although this would be a rare occurrence.

Participants were provided instructions about information reliability scores as follows. First, participants were informed that information sources above 50% reliability are *reliably right* because the displayed colour predicts the correct colour. In particular, participants were told that, for a blue square with 90% reliability, "*According to this square, the page colour should be blue. The source is 90% reliable, meaning there is a 90% chance that this piece of evidence shows the correct page colour*". Second, participants were explicitly told information sources with 50% reliability were uninformative because they are as likely to give the correct as the incorrect colour and are considered *unreliable information*. Participants were told that "*A blue square with 50% reliability indicates the page colour is blue, but it is only 50% reliable.50% reliability means this square gives you random information, as reliable as if the square's colour had been determined by flipping a coin*". Finally, participants were explicitly told that information sources below 50% reliability are informative but should be interpreted as evidence in favour of the opposite colour than they display and therefore are considered *reliably wrong* information. We provided the following explanation: "*A blue square with a 25% reliability is only 25% reliable. That's even less accurate than flipping a coin. Less than 50% reliability means the evidence provided by this square is reliably wrong. That is to say: if there is a 25% chance the square colour is correct, then there is a 75% chance that it is incorrect. So, while this square indicates the page colour is blue, likely it is actually red*".

On each trial, participants progressively scrolled down the page at their own pace using their mouse to reveal new sources and their predictions of the colour. In total, participants

could see six information samples before they made a response (Figure 1B). At the bottom of the page, two buttons corresponding to blue and red appeared on the left and right of the screen. Participants were asked to click a button to indicate which colour they believed would be more likely to be correct. The position of the blue-choice button and the red-choice button was randomised across participants. No time limit was imposed, and participants were encouraged to make their guesses as accurately as possible. Participants were given immediate feedback on whether their guess was correct or wrong. They proceeded to the next trial at their own pace by clicking the "next" button on the screen.

Each of the three experiments consisted of 6 blocks of 50 trials (300 trials in total). Participants could take a short break in between blocks as long as the duration of the experiment did not exceed 3 hours. A short version of our task will be available to play online.

Experiment 2

The apparatus, stimuli and task in the two introspective experiments were the same as in the first three experiments with the following differences: information reliability scores now varied between 50%, 55% and 65% in Experiment 2a and between 50%, 45% and 35% in Experiment 2b. We included one unreliable source and two reliably wrong sources in Experiment 2b to avoid potential contaminated effects by the presence of reliably right information. In addition to this change, we included a subjective estimate question in each trial. Immediately after guessing the colours, participants were now asked to provide a subjective rating to report the degree to which they felt they were influenced by the squares of a given reliability level (**Error! Reference source not found.**). In each trial, one information reliability level (e.g., 65%) was randomly selected and the following question appeared on the screen: "How did the 65% reliable squares influence your decision?". Participants rated their subjective sense of being influenced by the squares of that reliability level on a continuous scale ranging from "I responded opposite to the colour the squares indicated" (-50) to "No influence" (0) to "I responded according to the colour the squares indicated" (+50). Participants were instructed to use the full range of the scale and to make a rating uniquely based on the decision they just made. More specifically, we provided the following instructions "*After each response, we will ask you to evaluate how the squares of a given reliability level influenced the choice you just made. You will see a scale with a slider like the one below. You will have to indicate for your most recent choice to what extent you felt you followed the colour shown by those squares or chose the opposite colour of what those squares were suggesting.*" No time limit was imposed. A rating score below 0 indicated a negative influence by the colour of information

reliability, a score of zero indicated total independence and a score above 0 indicated a positive influence. Each of the two experiments consisted of 8 blocks of 36 trials (288 trials in total). Participants could take a short break in between blocks.

Data analysis

Models of optimal choice and participant's choice. Let C be the actual colour of the stimulus in the current trial, which can be either equal to B (blue) or R (red). We assume that $\Pr(C = B) = \Pr(C = R)$. The participants were instructed that both colours are equiprobable. Each information sample the participant receives can be seen as a signal s, providing a colour $c(s)$ and a probability $\pi(s)$. For instance, the sample "Blue with reliability 55%" is defined by *c(s)=B* and $\pi(s)$ =0.55. We denote by S the set of all pieces of information presented to the participant in a given trial, and by $S_B = \{s \in S | c(s) = B\}$ and $S_R = \{s \in S | c(s) = R\}$ the pieces of information with blue and red colours, respectively. To illustrate, assume that the participant observes three samples: "Blue with reliability 55%", "Red with reliability 50%" and "Blue with reliability 60%". We then have $S = \{s_1, s_2, s_3\}$, with $c(s_1) = B, \pi(s_1) = 0.55$, $c(s_2) = R, \pi(s_2) = 0.5$, $c(s_3) = B, \pi(s_3) = 0.60$. In that example, the set of Blue samples is $S_B = \{s_1, s_3\}$ and the set of Red samples is $S_R = \{s_2\}$. Note that, by definition, for all pieces of information s:

$$\Pr(C = c(s) | s) = \pi(s) \tag{1}$$

The posterior ratio corresponding to the stimulus colour given the information $(s_1, \dots, s_6)$ is then:

$$\frac{\Pr(C = B | s_1, \dots, s_6)}{\Pr(C = R | s_1, \dots, s_6)} = \prod_{s \in S} \frac{\Pr(C = B | s)}{\Pr(C = R | s)} \text{ (because the pieces of information are independent)}$$

$$= \left(\prod_{s \in S_B} \frac{\pi(s)}{1 - \pi(s)} \right) \left(\prod_{s \in S_R} \frac{1 - \pi(s)}{\pi(s)} \right)$$

where the last equality follows from equation (1). We thus have the following posterior log-odds

$$L(s_1, \dots, s_6) = \sum_{s \in S_B} \log \left(\frac{\pi(s)}{1 - \pi(s)} \right) - \sum_{s \in S_R} \log \left(\frac{\pi(s)}{1 - \pi(s)} \right).$$

An optimal Bayesian observer would thus choose Blue whenever $L(s_1, \dots, s_6) > 0$, and Red otherwise. See Figure 1C.

The decision maker might be, however, biased. A simple way to model such a bias is to assume that she linearly distorts the log-odds corresponding to each piece of information (Zhang & Maloney, 2012; Zhang et al., 2020). In other words, she would compute the following subjective log-odd ratio:

$$\tilde{L}(s_1, \dots, s_6, a, b) = \sum_{s \in S_B} \left(a \log \left(\frac{\pi(s)}{1 - \pi(s)} \right) + b \right) - \sum_{s \in S_R} \left(a \log \left(\frac{\pi(s)}{1 - \pi(s)} \right) + b \right),$$

where parameter $a \geq 0$ reflects the participant's sensitivity to the probabilistic information, and b is interpreted as a measure of her "presentation bias", i.e., to which extent she is influenced by the mere presentation of a given colour (Figure 3). The Bayesian optimal corresponds to $a = 1$ and $b = 0$. If, for instance, $a = 0$ and $b > 0$, the participant does not take at all into account the reliability of the information, and simply counts the number of samples corresponding to each colour. Crucially, it turns that $\tilde{L}$ can equivalently be written as:

$$\tilde{L}(s_1, \dots, s_6, a, b) = \sum_{s \in S_B} \log \left(\frac{\varphi(\pi(s), a, b)}{1 - \varphi(\pi(s), a, b)} \right) - \sum_{s \in S_R} \log \left(\frac{\varphi(\pi(s), a, b)}{1 - \varphi(\pi(s), a, b)} \right),$$

where:

$$\varphi(\pi(s), a, b) = \frac{\gamma \pi(s)^a}{\gamma \pi(s)^a + \left(1 - \pi(s)\right)^a}$$

and $\gamma = e^b$. The function $\varphi(\pi(s), a, b)$ is interpreted as a subjective probability distortion function (Gonzalez & Wu, 1999). In other words, the biased log-odd can equivalently be seen as an unbiased log-odd applied to distorted probabilities or a biased log-odd applied to actual probabilities. In turn, distorted probability can be interpreted as the weight the participant gave to each information reliability level in the decision process.

The subjective log-odd might be further distorted by a memory leak, implying that each piece of information is weighted by its order in the presentation sequence (Figure 3). To formalize this idea, let $\rho(s)$ denotes the rank order of the piece of information s (in other words, $\rho(s_i) = i$). We further define a subject-dependent weight function w, that assigns a non-negative weight to each piece of information, and we normalize it by requiring $w(6) = 1$. We then obtain:

$$\tilde{L}(s_1, \ldots, s_6, a, b, w) = \sum_{s \in S_B} w\left(\rho(s)\right)\left(a\log\left(\frac{\pi(s)}{1-\pi(s)}\right) + b\right) - \sum_{s \in S_R} w\left(\rho(s)\right)\left(a\log\left(\frac{\pi(s)}{1-\pi(s)}\right) + b\right)$$

Finally, we model the fact that the decision process might be noisy by assuming that the actual choice follows a softmax rule (Figure 3). Thus, the decision maker chooses Blue with probability:

$$p(blue) = \frac{1}{1 + e^{-\tilde{L}(s_1, \ldots, s_6, a, b, w)}}$$

In a softmax rule, an inverse temperature parameter tunes decision stochasticity. We fixed this parameter to 1 due to a problem of parameter identifiability. If we found a difference in the values of a or b parameter between the experiments, it may indicate that two groups of participants were different in sensitivity to the probabilistic information or in presentation bias. However, because of this parameter constraint, we cannot rule out the possibility that two groups of participants were different in decision stochasticity.

We tested the assumption of reliability distortion and the assumption of memory leak by a factorial model comparison (van den Berg et al., 2014). The first model was the BDT model, representing the behaviour of an optimal Bayesian observer who does not distort the reliability probabilities and has a perfect memory capacity (no free parameter). This is equivalent to constraining $a = 1$, $b = 0$, and $w(p(s)) = 1$. In the second model, we introduced memory leak solely, keeping $a = 1$ and $b = 0$, allowing only the following set $\Theta = \{w(1), w(2), w(3), w(4), w(5)\}$ of free parameters to change. Conversely, the third model introduced distortion in reliability solely, using a set of free parameters $\Theta = \{a, b\}$. In the last model, we introduced both memory leak and distortion in reliability, using a full set of free parameters $\Theta = \{a, b, w(1), w(2), w(3), w(4), w(5)\}$.

For each model, we fitted the model probability of choosing blue to the participant's choice data using a Bayesian hierarchical modelling approach. The four models were fitted using Hamiltonian Monte Carlo sampling as a Markov Chain Monte Carlo method (MCMC) in Stan (Carpenter et al., 2017; StanDevelopmentTeam., 2023) and RStan (version 2.32.6). MCMC approximates the posterior distribution of the free parameters of the model. We estimated the means of group parameters, the variances of group parameters and individual parameters for each participant. The parameter a was constrained between 0 and 20, while memory leak parameters were constrained between 0 and 2. No constraint was imposed on b. Models were fit from four parallel chains with 2,000 warm-up samples, followed by 2,000

samples drawn from converged chains. Model comparison was performed using the *loo* package in R, which uses a version of the leave-one-out estimate that was optimized using Pareto smoothed importance sampling (PSIS) (Vehtari et al., 2017). *loo* estimates the expected log pointwise predictive density (elpd) without one data point using posterior simulations. This index is a measure of the out-of-sample predictive accuracy, i.e., how well the entire data set without one data point predicts this excluded point. PSIS-loo is sensitive to overfitting: neither more complex models nor simpler models should be preferred by the inference criterion (Danwitz et al., 2022).

Measuring the influence of information reliability on choice (Experiment 1 and 2). We performed a regression analysis to estimate the influence of three levels of explicit information reliability cue on the participant's binary action choices. The participant's choice would be ultimately determined by an overall difference between the evidence that favoured the blue option and the evidence that favoured the red option in a given sequence. However, we could estimate how each of the three information reliabilities partially affected the choice using a regression approach. To compute the difference in the evidence values, we counted, for each sequence of six sources, how many blue sources and red sources were shown respectively by each information reliability level. We then computed the net number of samples in favour of each colour by calculating the difference between blue and red for each information reliability level. For instance, if a participant had the following sequence: 65% blue, 55% blue, 55% red, 55% red, 50% blue and 50% red, 65% reliability had a net value of +1 blue source and 0 red source, 55% reliability had a net value +1 blue source and +2 red sources, 50% reliability had a net value of +1 for each colour. Therefore, the net number displayed at 65% reliability is +1 for blue, +1 for red at 55% reliability and 0 at 50% reliability. A net number of sources between blue and red was counted separately for 50%, 55% and 65% in Experiment 1a, 50%, 45% and 65% in Experiment 1b,50%, 55% and 35% in Experiment 1c, 50%, 55% and 65% in Experiment 2a and 50%, 45% and 35% in Experiment 2b. We performed the logistic regression to predict the participants' binary choices, with running separately for the first three decision-making experiments and the second two metacognition experiments. We used a categorical variable *exp* to represent the experiment (1a, 1b or 1b in the first experiment; 2a or 2b in the second experiment). We then coded *source 1* as the net number of sources with 50% reliability, *source 2* as the net number of sources with either 55% reliability (in Exp 1a, Exp 1c and Exp 2a) or 45% reliability (in Exp 1b and Exp 2b) and *source 3* as the net number of sources with

either 65% reliability (in Exp 1a, Exp 1b and Exp 2a) or 35% reliability (in Exp 1c and Exp 2b). Finally, for each set of the experiments (Experiment 1a-1c or Experiment 2a-2b), we used "lme4" package (Bates et al., 2015) to perform mixed-effects logistic regression with the following formula: glmer (*choices* ~ (1 | *ID*) + *exp* × *source 1* + *exp* × *source 2* + *exp* × *source 3*). The intercept varied between participants *ID* as a random effect. See Figure 2B&C.

Measuring the subjective influence of information reliability (Experiment 2 only). A regression approach allows us to characterise discrepancies between human and optimal performance (Dal Martello et al., 2023; Ota et al., 2024; Ota & Maloney, 2024). We performed a linear regression analysis to estimate how the rating of introspective reports was correlated to the level of the reliability of information. We reasoned that the strength of the introspective rating would be determined by the information reliability per se as well as by the net number of squares present in that trial for the squares of the reliability level, and by the direction in which it influenced the decision (following or opposing the colour of sources). Suppose the participant was presented with two blue squares of 65% reliability, one red square of 65% reliability and three red squares of 50% reliability. If the participant chose blue and then was asked to report the influence of 65% reliability squares on their choice, the participant would report that they followed the colour displayed by the 65% squares (i.e., positive influence) because their blue choice was likely supported by two blue squares of 65% reliability. In another example, suppose the following sequence was presented: two blue squares of 35% reliability, one red square of 35% reliability and three red squares of 50% reliability. If the participant chose red and then was asked to report the influence of 35% reliability squares on their choice, the participant would report that they opposed the colour displayed by the 35% squares (i.e., negative influence) because their red choice was likely supported by two blue squares of 35% reliability.

Therefore, for each level of information reliability in a given sequence of six sources, we counted 1) how many sources were *congruent* with the colour chosen by the participant and 2) how many sources were *incongruent* with the chosen colour. We then computed a net difference between the congruent and incongruent sources at each reliability level. For instance, if a participant had the following sequence: 50% red square, 55% blue square, 55% blue square, 65% red square, 65% blue square and 50% red square, then the 65% reliability displayed 1 blue source and 1 red source, 55% reliability displayed 2 blue sources and 50% reliability displayed 2 red sources. If the participant chose blue, this means that two 55%

reliable sources were congruent with the colour the participant chose, and two 50% reliable sources were incongruent with the chosen colour. In such a trial, a net number was 0 at 65% reliability, 2 for congruent sources at 55% reliability and 2 for incongruent sources at 50% reliability. Therefore, a net number between congruent and incongruent sources was 0 at 65% reliability, 2 at 55% reliability and -2 at 50% reliability. As such a net number between congruent and incongruent sources was counted separately for 50%, 55% and 65% in Experiment 2a and 50%, 45% and 35% in Experiment 2b. We performed the linear regression to predict the participants' instrospective reports, separately for Experiment 2a and Experiment 2b. We used a categorical variable *level* to represent which reliability was chosen for the introspective report for a given trial (50%, 55% or 65% in Exp 2a; 50%, 45%, 35% in Exp 2b). We then coded *source 1* as the net number between congruent and incongruent sources with 50% reliability, *source 2* as the net number with either 55% reliability (in Exp 2) or 45% reliability (in Exp 2b) and *source 3* as the net number with either 65% reliability (in Exp 2a) or 35% reliability (in Exp 2b). Finally, for experiment, we performed mixed-effects linear regression with the following formula: lmer (*reports* ~ (1 | *ID*) + *level* × *source 1* + *level* × *source 2* + *level* × *source 3*). The intercept varied between participants *ID* as a random effect. See Figure 5 and Supplementary Figure 4.

Competing interests

The authors declare no competing interests.

Author's contributions

Acknowledgments

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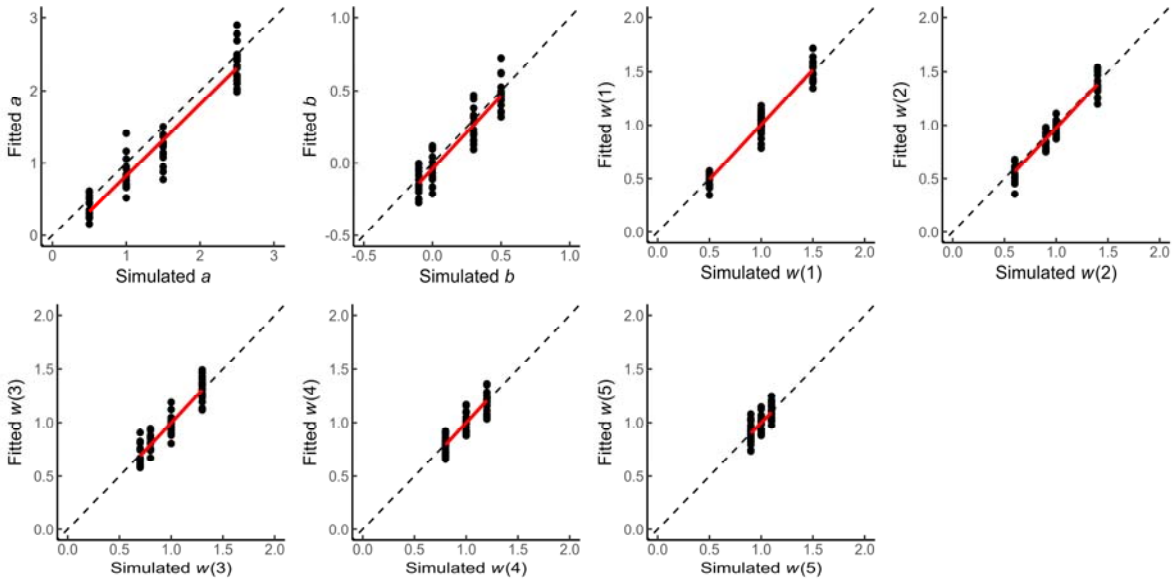
Data and code availability

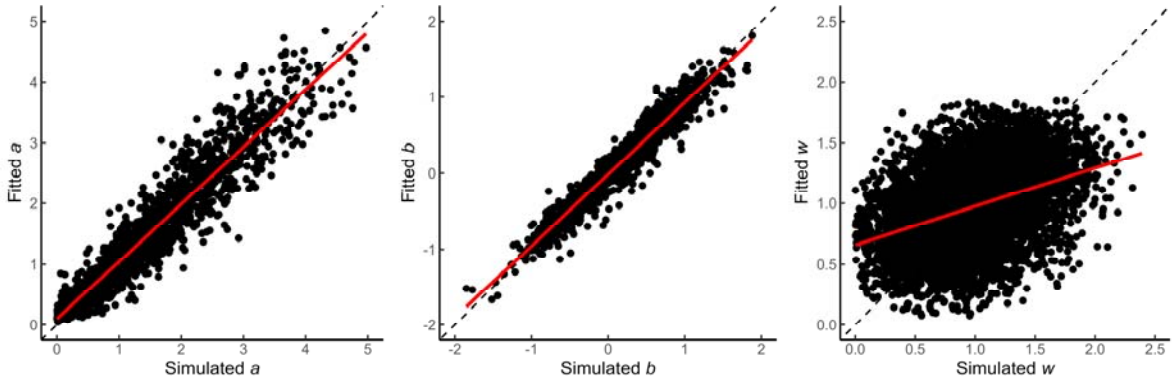
The data frame for a representative participant will be posted. The data frames for all the participants and the codes used to generate the figures will be posted.

Supplementary Information



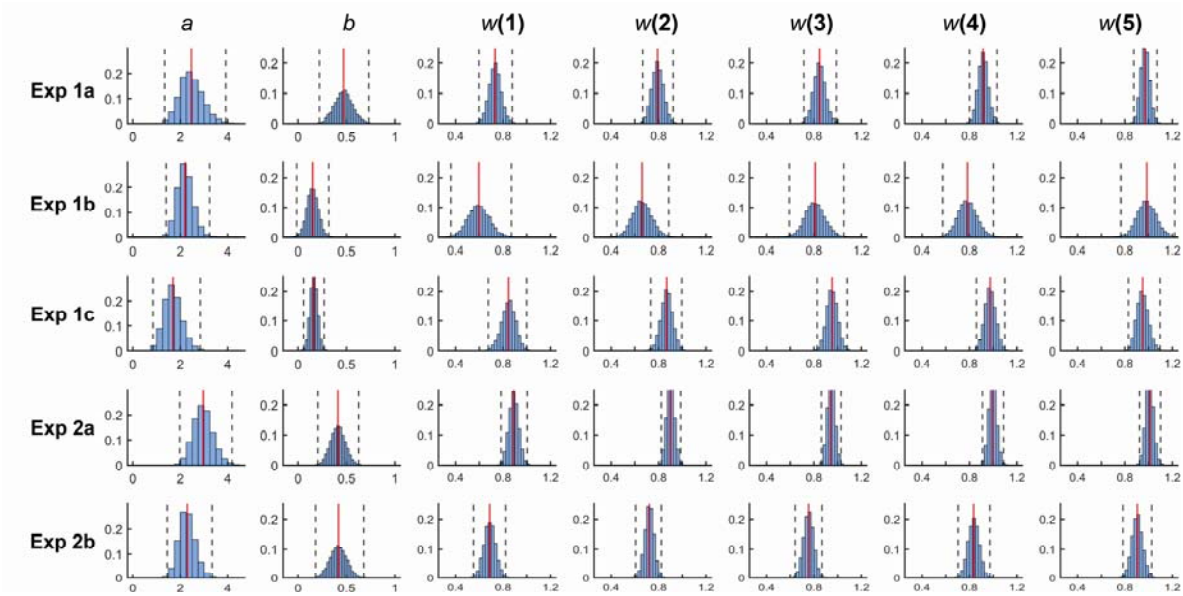
Supplementary Figure 1. Recovery of group-level parameters.

A. Parameter recovery of sensitivity to the probabilistic information. **B.** Parameter recovery of presentation bias. **C-G.** Parameter recovery of sequential weights (i.e., memory leak). Scatter plots show the correlation of the simulated values (i.e., the input values to the simulation) and the recovered values obtained in the fitting process. Black dashed lines show diagonal lines for a perfect parameter recovery. Red lines show the linear regression lines.



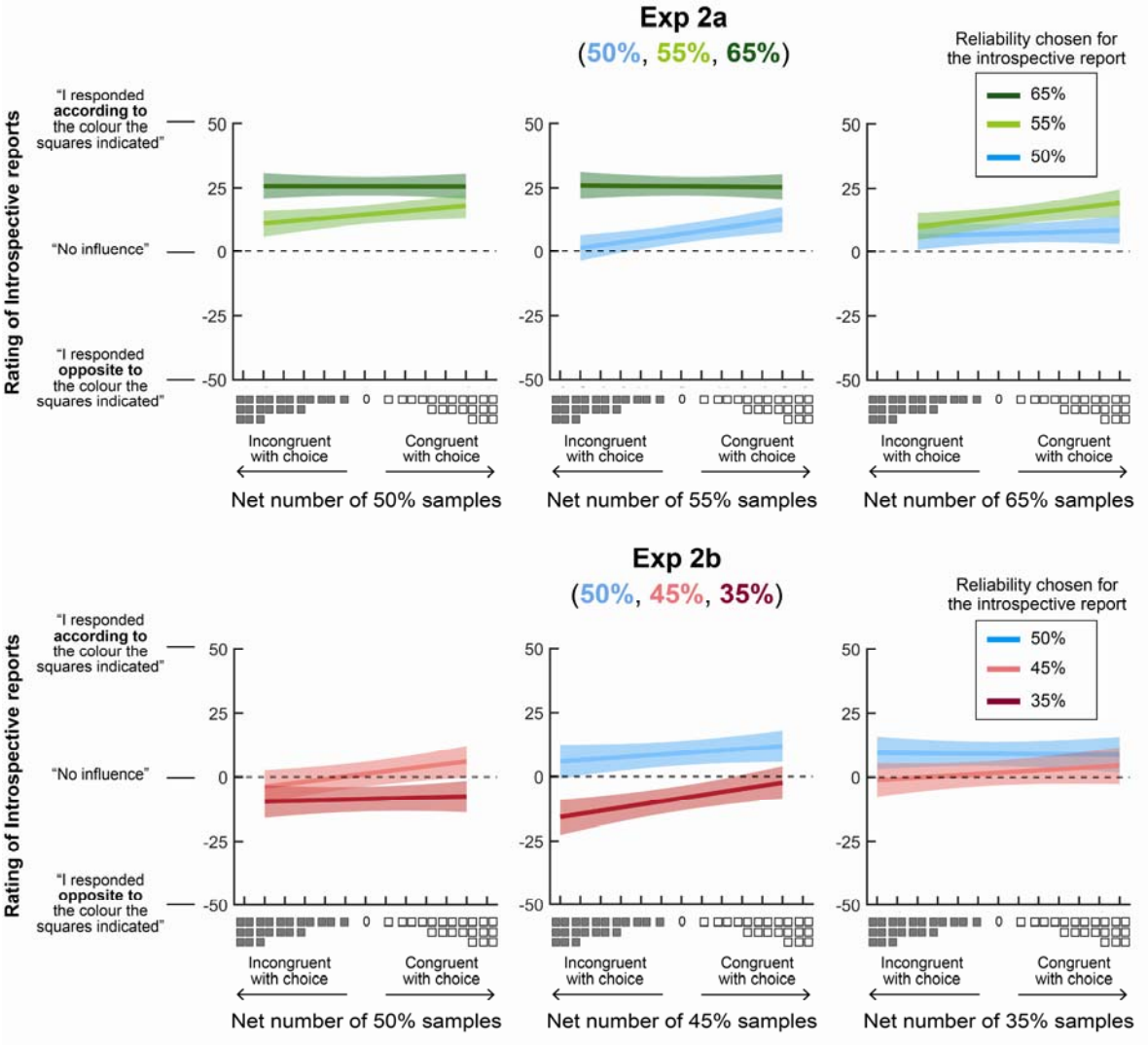
Supplementary Figure 2. Recovery of individual-level parameters.

A. Parameter recovery of sensitivity to the probabilistic information. **B.** Parameter recovery of presentation bias. **C.** Parameter recovery of sequential weights. Scatter plots show the correlation of the simulated values (i.e., the input values to the simulation) and the recovered values obtained in the fitting process. Black dashed lines show diagonal lines for a perfect parameter recovery. Red lines show the linear regression lines.



Supplementary Figure 3. Full posterior samples of group-level parameters.

We retrieved the estimates of means of the seven group-level parameters from a Bayesian hierarchical model fit of the full model. Each histogram provides a proxy of the posterior distribution of the parameter value. Red lines denote the average of the posterior distribution while dashed lines denote the 99% confidence intervals.



Supplementary Figure 4. Marginal effects on the introspective reports.

See the caption in Figure 5. A flat slope of the regression indicates that the reliability sources that were not chosen for the introspective reports (x-axis) have little effect on the subjective feeling when reporting the influence of the chosen level of reliability on choice (colored lines).

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