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Commentary

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'Are you sure?' The importance of understanding your own sensory uncertainty

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Γνῶθι σεαυτόν ('Know thyself', inscription on Temple of Apollo, Delphi)

Human perception is often unreliable. When interacting with everyday objects, we may not notice. But when placed in a novel environment, such as during a walk on a foggy evening, we quickly realize how fallible our senses can be. Understanding our own perceptual uncertainty is critical for making sound decisions based on the incomplete and noisy information available to us across multiple senses.

In Hong *et al*. [1], the authors examined how accurately human choices in a perceptual task reflect their own perceptual variability. This is interesting because, within a widely used Bayesian framework [2], there is an assumption that the decision-maker has learnt, or somehow has access to, the uncertainty of their own perceptual estimates, a prerequisite for optimal inference.

The standard version of the 'Bayesian brain' hypothesis assumes that all inference, prediction and decision-making follows a Bayesian decision theoretical framework, i.e. that the brain is universally optimized for decision-making under uncertainty. In practice, however, it is well understood that the nervous system faces numerous constraints that render this claim too simplistic [3]. Indeed, studies have found a range of experimental scenarios in which behaviour deviates from optimality [4]. Nevertheless, many studies in human and mammalian perception have found a near-optimal integration of information in both behavioural and neural recordings [5–8], suggesting that, in a number of perceptual tasks, uncertainty is correctly taken into account.

Across more than 20 years of research, a large number of studies have tested Bayesian models of behaviour across various perceptual systems and tasks. Although Bayesian models have often shown excellent abilities to predict and explain aspects of behaviour, one limitation in the great majority of these studies is that some parameters in the model are potentially confounded. For example [9], in many studies, the same behaviour is predicted by either (i) an over-reliance on an unreliable cue (showing uncertainty is not properly taken into account, see [4] for a review of over-reliance) or (ii) some other source of bias or prior assumption. The only way to get around this experimentally is to use a large number of trials, with a large number of carefully chosen conditions, across multiple experiments, which is technically demanding (for an example of this approach, see [10]).

Hong *et al.* met this challenge by testing judgements about auditory and visual stimuli in a set of human participants, all of whom performed each of four well studied experimental paradigms. Specifically, they were tested on temporal order judgements (Did A happen before or after B?), spatial discrimination (Is A left or right of B?), spatial localization (Where is A?) and causal judgements (Do A and B have a common cause, or did they occur independently?).

The authors fitted parameters of a single Bayesian model to all behavioural data, forcing some parameters (e.g. visual uncertainty or the width of the central prior) to be fixed for a participant across experimental conditions,

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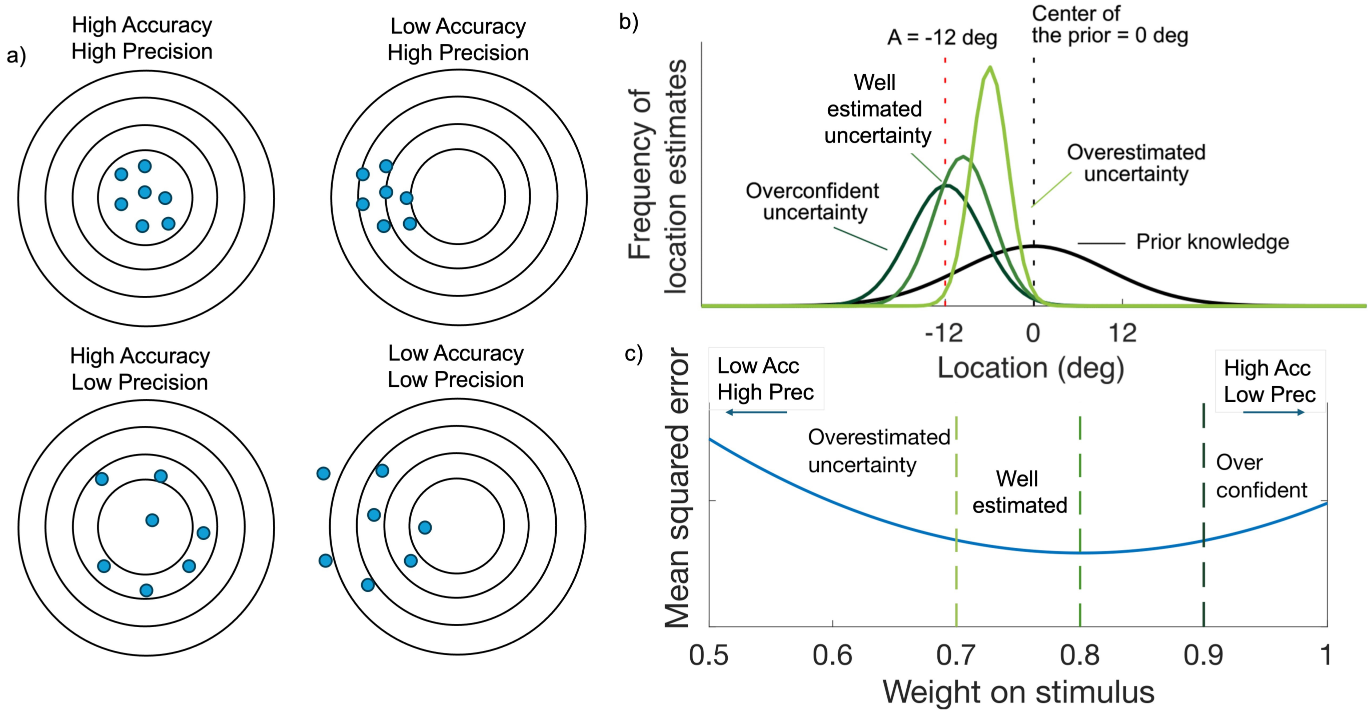

Figure 1. There is a tradeoff between the accuracy and the precision of a participants responses, dependant on whether they over-estimate their uncertainty, or are over-confident. (a) High accuracy means the *average* error is small, i.e. on average close to the centre of the target. High precision corresponds to a low *variability* in responses. (b) Distributions of auditory-location estimates (responses) given an auditory stimulus presented alone at −12°, assuming the observer based their perceptual inference on an overconfident estimate of uncertainty (dark green) or a well estimated value of uncertainty (green), or overestimated their uncertainty (light green) associated with auditory spatial perception. Fig. S11a from Hong *et al.* [1]. (c) The mean squared error in the task is the lowest if the subject uses a well estimated value for the confidence, but increases if they either overestimate their uncertainty (underconfident, low accuracy, high precision on the left) or overestimate their confidence (high accuracy, low precision on the right).

while allowing other parameters (e.g. auditory location-dependent bias) to be dependent on the experimental conditions.

Importantly, they specifically allowed separate parameters for the subjects' assumed auditory uncertainty (used in the likelihood function of the Bayesian model) and for the subjects' auditory variability (used to model the variability in internal signals). In most studies, these two parameters are assumed to be identical, i.e. that subjects have a veridical understanding of their own uncertainty.

By performing model comparison, the researchers could test whether participants acted as if they over- or underestimated their own internal variability. Such over- or underconfidence could arise if the nervous system has not correctly learnt its own uncertainty, or has not correctly incorporated the true uncertainty in its perceptual judgements.

Contrary to the standard Bayesian model assumption, the authors found that participants' responses to auditory stimuli did not reflect the uncertainty in their own perceptual system. Instead, they underestimated their own audiovisual temporal and auditory spatial uncertainty by, on average, a factor of 2 or more. In contrast, there was no evidence for over- or underestimation of the visual spatial uncertainty.

These results open up two key, non-mutually exclusive possibilities: (i) people do not know their own temporal and spatial auditory uncertainty, instead assuming a smaller level of uncertainty, i.e. being overconfident in their own perceptual system. Alternatively, it could be that (ii) people are not following the Bayesian decision strategy. Crucially, in either case, people are behaving *as if they are more certain than they really should be*—whether because the underlying representation of uncertainty is wrong or because it is being used incorrectly to make decisions.

If the typical participant indeed underestimates their perceptual uncertainty, this will have implications for the type of errors they make: better accuracy, but worse precision (see figure 1a for explanation of terms). As shown in figure 1b, when overconfident about their uncertainty, a participant will rely less on the prior.

In other words, the average response will be close to the true stimulus, but across trials, responses will be more variable. A typical way of quantifying error is through the mean squared error, between the estimated and true locations $(s_{\text{est}} - s_{\text{true}})^2$. Figure 1c shows that the mean squared error increases when a participant is either overconfident or overestimates the uncertainty.

An important implication is that different perceptual systems in the brain may have different approaches towards inference. The results reported here suggest that the visual system works with a veridical understanding of its own uncertainty, whereas the auditory system does not. Does this mean that the visual system is special, possibly owing to the encoding of spatial properties by tuned populations of neurons in visual cortex [11]? Do we just have more experience with visual information in the environments presented to the participants in the study? It has generally been the case that, for typical participants, the perception of a visual stimulus is more reliable in the spatial domain (i.e. in localization), while the perception of an auditory stimulus is more reliable in the temporal domain (e.g. in temporal order judgements). This suggests differences in the perceptual uncertainty that is task-specific.

However, the experiments by Hong *et al.* covered both spatial and temporal tasks, and found for both that most (10 out of 13) participants did not correctly account for their auditory uncertainty. Hence, it is not just the case that task-specific performance separates visual from auditory perception; there seem to be genuine differences in how uncertainty is processed, at least for typical participants.

It is still unclear whether special populations (expert blind echolocators [12], professional musicians, athletes [13]) have better internal representation of their perceptual uncertainty, a topic for future work.

This study adds to a growing literature on understanding reasons for sub-optimal behaviour in perception. Previous work has suggested that sub-optimal or (non-optimal) behaviour could also be due to a number of other factors, including incorrect priors or failures to take into account reward functions (see [4] for a review).

Another recent proposal [14] is that the nervous system processes uncertainty more efficiently when the information is presented in a modality that more naturally encodes uncertainty through neurons. As an example, for visual stimuli, uncertainty may be neurally represented through population coding [15]. In contrast, for information presented externally to such a system (e.g. as verbal information without a natural population coding), this kind of encoding will not be available. Hence, uncertainty transmitted verbally will be either incorrect or not accessible to the parts of the nervous system that perform Bayesian inference. This is, of course, related to discussions about when and why classical/verbal decision-making differs from perceptual decision-making [16,17].

The study by Hong *et al.* is in line with this broad idea that different systems in the brain are specialized for decision-making under uncertainty. Their study suggests the interesting possibility that, even within simple perceptual tasks, the auditory system may be encoding uncertainty differently from how the visual system does.

Understanding one's own uncertainty is of high general importance. Suppose a government agency needs to make decisions based on different reported predictions of the effects of future climate change. In that case, it needs to be able to assess the uncertainty (or reliability) of each report in order to create a coherent understanding that can support good policymaking. The nervous system will not have specific neural pathways tuned towards assessing the predicted effects of climate change, and certainly does not have neural coding especially tuned for this. Instead, it will have to rely on more general cognitive systems. It is possible that such systems can be trained to approach optimality, or it is possible that information can be presented so as to increase optimality, but these are still open questions.

The experiments still leave a number of questions unanswered. In order to limit the computational complexity, the authors had to limit the number of parameters in the Bayesian model to explore (e.g. by assuming that the visual uncertainty did not vary across experiments). This is a limitation of the modelling, as it is an untested assumption in this study. Given the existing data (available open source), other researchers can potentially examine a larger parameter space, including testing different sub-optimal variants of the model. It is, of course, also possible that a more advanced Bayesian model, or even a non-Bayesian model, may be able to explain the data better.

Overall, this study highlights the limitations of human auditory and audiovisual perception (at least in untrained individuals) and reminds us all to be aware of our own uncertainty.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. This article has no additional data.

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. U.B.: conceptualization, formal analysis, investigation, writing—original draft, writing—review and editing; M.N.: conceptualization, investigation, writing—original draft, writing—review and editing.

Both authors gave final approval for publication and agreed to be held accountable for the work performed herein.

Conflict of interest declaration. We declare we have no competing interests.

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