Metacognitive insight into decision caution

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Abstract

Perceptual decisions are accompanied by metacognitive experiences, such as the sense of confidence, that closely follows the speed and accuracy of each decision. Confidence can inform a general sense of performance to facilitate strategic adaptation of decision-making. Metacognitive insight into specific latent decision process parameters, however, could improve such adaptation, because it would allow decision-makers to pinpoint the source of errors and adapt accordingly. Here, we assessed insight into one key parameter generally thought to be under strategic control, the decision threshold. Participants decided on the direction of a random dot motion (RDM) stimulus in two conditions (cautious versus impulsive instructions). After each decision, they rated their sense of caution. As expected, decisions were faster and less accurate in the impulsive than in the cautious condition, and metacognitive ratings of caution were sensitive to these conditions. Modeling indicated that caution ratings reflect genuine insight into the state of the decision boundary, as opposed to other latent parameters or simply tracking response times. A hierarchical DDM will be used to asses this relationship on a single-trial basis.

Keywords: perceptual decision making; metacognition; drift diffusion model; caution

Introduction

Perceptual decisions are accompanied by a sense of confidence, which closely follows the speed and accuracy of the decision (Aitchison et al., 2015; Dotan et al., 2018; Kiani et al., 2014). This sense of confidence can be used to inform subsequent decision processes on similar decisions, strategically adapting them to improve performance (Desender et al., 2019). However, confidence can only indicate the need for adaptation, but not which type of adaptation is most appropriate.

Having metacognitive insight into the latent variables underlying the decision process would be more informative for to pinpointing the source of performance decrements, e.g. due to bias or impulsiveness. Latent variables underlying decisions are well described by popular models of perceptual decision making, such as the drift diffusion model or DDM (Ratcliff, 1978). This model contains latent parameters which jointly explain the speed and accuracy of perceptual decisions. Here, we studied whether human participants have metacognitive insight into the state of the decision threshold – a key DDM parameter governing the tradeoff between decision speed and accuracy and generally thought to be under strategic control.

Methods

Participants (n = 38) decided on the direction of a random dot motion (RDM) stimulus in two different conditions: one in which they were instructed to be impulsive and one in which they were instructed to be cautious. After each decision, they rated their caution on a scale between 0 and 100.

Because response times (RTs) correlate with the height of the boundary, which itself depends on the caution-instruction, we ran simulations to see what pattern of results can be expected if caution ratings are simply based on RTs, if they are based on the true state of the boundary, or if they are based on any of the other latent variables. In these simulations, caution ratings reflected a noisy read-out of either of the 4 parameters or response times. We used a linear mixed model to investigate which factors of the decision-making process contributed to the caution ratings.

Results

Model simulations showed that if caution ratings are a noisy read-out of response times (fig. 1A) or of the state of the boundary (fig. 1B) - but not if they are a read-out of any of the other latent parameters (fig. 1ADE) - the simulated caution ratings monotonically depend on response times. Critically, however, caution ratings should also be sensitive to the accuracy of a decision if they genuinely track the state of the decision boundary, not just response times (fig. 1B). To examine which of these scenarios is characteristic of the caution ratings employed by human participants, we next turned to the empirical data. As expected, decisions were faster and less accurate in the impulsive than in the cautious condition, and metacognitive ratings of caution were sensitive to the conditions (fig. 2). More importantly, the relationship between response time and caution rating from observed data closely resembled the predictions from the boundary model in both the cautious and impulsive condition (fig. 2). In line with this, the linear

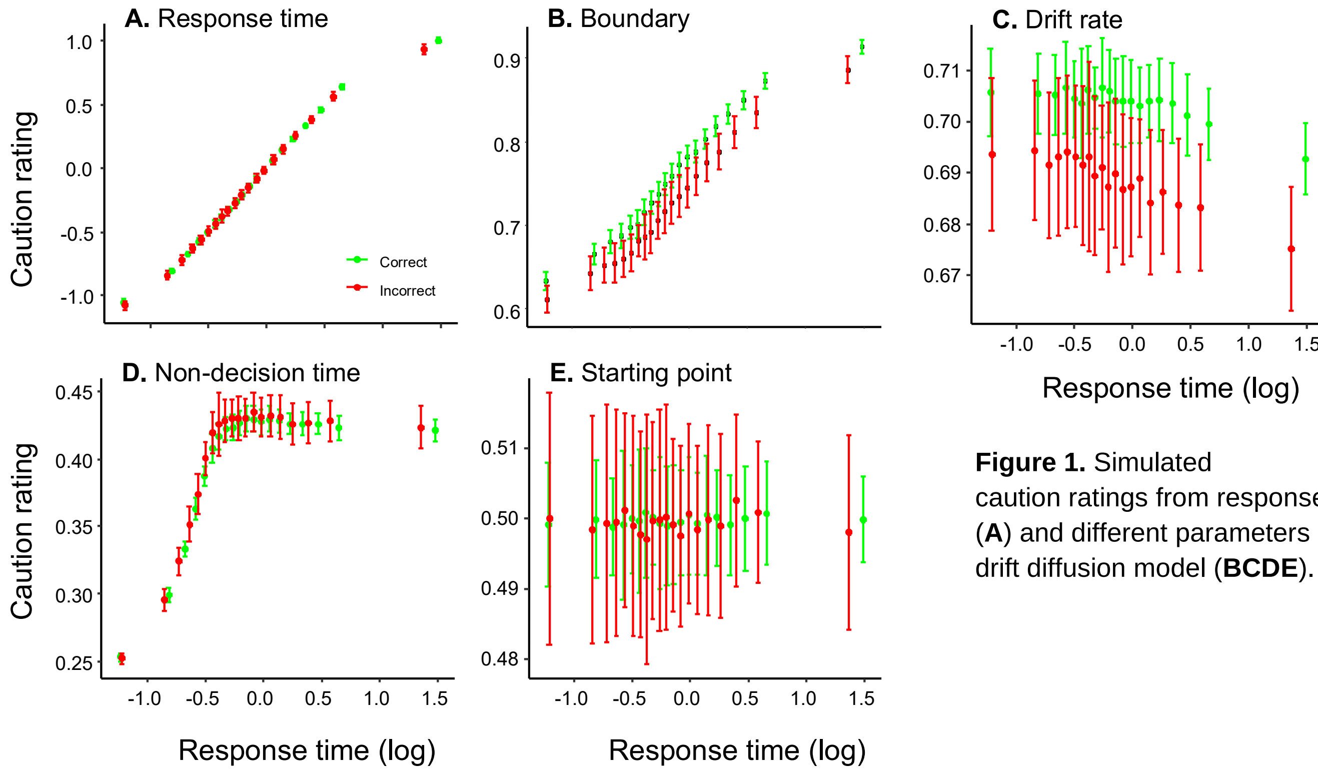

Figure 1. Simulated caution ratings from response times (**A**) and different parameters of the drift diffusion model (**BCDE**).

mixed models revealed a dependency of the caution rating on both response time ($\chi^2(1) = 98.883$, $p < .001$) and accuracy ($\chi^2(1) = 8.892$, $p = 0.003$), but no interaction between response time and accuracy ($p > 0.050$). These findings demonstrate that participants indeed have metacognitive insight into their decision threshold, instead of simply basing their caution rating on an observable variable such as response time.

Discussion

We conclude that people have metacognitive insight into their decision threshold. Next, we plan to use a hierarchical DDM to test whether empirical caution ratings are associated with the state of the decision threshold at a single-trial level. We expect to find that trial-by-trial caution ratings closely track fluctuations in the decision threshold.

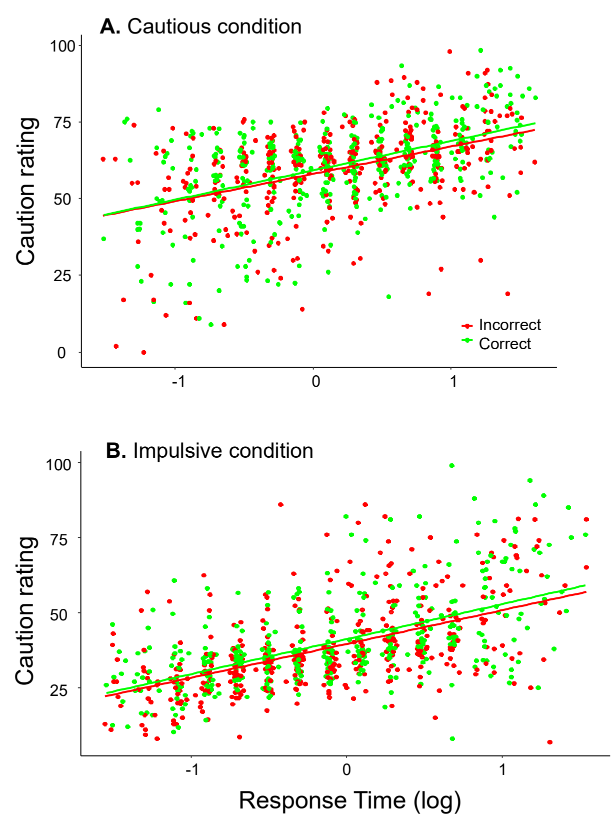

Figure 2. The observed relationship between response time and caution rating for correct and incorrect trials in the cautious (**A**) and impulsive (**B**) condition.

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