Perceptual Choices and Confidence Judgements can be Modelled as a Single Accumulation Process

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Abstract

Evidence accumulation can continue after a choice is made to incorporate new evidence and inform subjective confidence ratings, but we do not know how this post-choice evidence accumulation process differs from the one that informed the initial choice. Existing models disagree regarding whether the post-decision process is a continuation of the initial choice process or reflects a distinct one. In addition, current models disagree on the question of whether post-choice accumulation processes are subject to time-based or boundary-based stopping rules. We implemented these alternative mechanisms across four classes of models and fit them to human data from a task with a speed/accuracy trade-off applied only to the post-decision confidence rating stage, via a deadline. Speed-pressure decreased confidence-RT, certainty, metacognitive accuracy, and changes-of-mind (CoM). The four classes of models were able to fit the data well, but Boundary-Based Stopping Rules fit the data better than the Time-Based Stopping Rules, as the latter were unable to replicate the pattern of decreasing certainty for slower confidence-RTs. However, the behavioural modelling did not conclusively favour one Boundary model over the other. We therefore compared the evolving Decision Variable with a neural marker of evidence accumulation, the Centro-Parietal Positivity (CPP), to further distinguish these two similar models. The Shared-process Boundary-based model was able to replicate qualitative effects of Certainty and CoM on the CPP, while the Distinct-Boundary model could not. We suggest that post-decision evidence accumulation is boundary-based rather than time-based, and shares information with the initial-decision process rather than being a distinct accumulation mechanism.

Keywords: confidence; CPP; ERP; EEG; decision-making; meta-cognition;

Introduction

Many models exist that allow post-decision evidence to inform confidence ratings, often via an evidence accumulation process similar to the initial decision, but with different mechanisms for starting and stopping this process. A Time-Based Stopping Rule (Pleskac & Busemeyer, 2010), where post-decision accumulation continues for a set amount of time, can account for many patterns seen in human data but fails to replicate a negative relationship between confidence-RT and confidence-ratings. A Boundary-Based Stopping Rule which can collapse over time does capture this negative relationship (Herregods et al., 2023). However, these two classes of models can make very similar behavioural predictions. Additionally, models can differ in how they treat the start of the post-decision process; as a Distinct process from the initial decision termination, or as a Shared process which continues from where the initial boundary-crossing occurs. Again, these two processes can produce similar behavioural effects. Neural signals offer a way to disambiguate behavioural model mimicry. The Centro-Parietal Positivity (CPP) is a potential marker of evidence accumulation which shows a rise-to-peak activity before a decision is made, reaches a lower peak on slower trials (consistent with a collapsing-boundary), and scales with confidence ratings both before and after a decision (Grogan et al., 2023). Here we measured the CPP on a random dot motion task with a speed/accuracy trade-off induced solely at the post-decision stage. We fit models with Time/Boundary Based Stopping Rules and Distinct/Shared processes to the behavioural data and used the CPP as a model validation to further disambiguate between these highly similar models (see Figure 1A).

Methods

We used a large trial-number, small-N design, collecting 2160 trials from 14 participants. Participants performed a random dot motion discrimination task with confidence ratings, and we manipulated the deadline (700ms or 3000ms) for the confidence rating to induce a speed/accuracy trade-off only at the post-decision stage. We fit four types of models to the data, which are visualized in Figure 1.

Results

The BIC greatly favoured the Boundary-Based Stopping Rules over the Time-Based (ΔBIC=782), with a smaller preference for the Distinct-process over the Shared-process (ΔBIC=274). All four types of models were able to replicate the overall confidence-RT distributions, and most of the speed/accuracy effects were captured to some extent. The Time-Based models could not replicate the decreasing certainty and accuracy for slower confidence-RTs (Figure 1B), while the Distinct-Boundary model was better at reproducing the speed-pressure effects on CoM and confidence, and the Shared-Boundary model was better at capturing the AUROC2 difference.

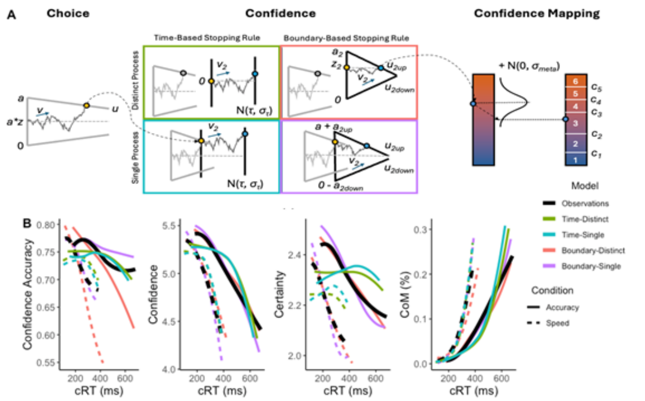

Figure 1*: A. The initial decision was modelled using a drift diffusion model, where noisy evidence accumulates with a certain drift rate (v) until hitting a collapsing boundary (controlled by u) with accumulation starting at the unbiased point a*z. (middle) All post-decisional models included parameters for the rate of accumulation (v2). In Time-based models, the time of stopping was determined by a mean deadline time (τ) with some variability (στ). In boundary-based models, the time of stopping was determined by collapsing boundaries, controlled by parameters related to boundary heights (a2up and a2down for the Shared variant, a2 and z2 for the Distinct variant), and corresponding collapse rates (u2up, u2down). (Bottom right) Finally, in all models, evidence was translated into a six-points scale using a metacognitive noise parameter (σmeta) and five confidence criteria (c1 to c5). Non-decision components not displayed. (B) Confidence accuracy, confidence, certainty, and change-of-mind (CoM) probability as a function of confidence-RT (smoothed using loess regression).*

Given that the two Boundary models provided quite similar fits (ΔBIC=94), we validated them against a measure not included in the model fitting – a neural signature of evidence accumulation, the CPP. The Shared-Boundary model was better at reproducing the effects of Certainty and CoM on the CPP than the Distinct-Boundary model (Figure 2), capturing the growing effect of Certainty before the initial RT and the positive CoM effect after the initial response, which both remain until confidence RT. The Distinct-Boundary model had opposite directions of these two effects, as confirmed by time-derived regression analyses. This suggests that the Shared-Boundary model better captures the metacognitive processes in these decisions, as measured by the CPP.

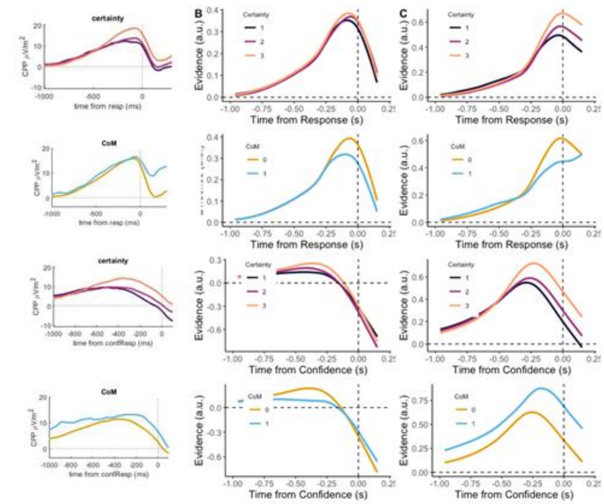

Figure 2*: Observed CPP & Simulated Decision Variable. Panels show the effects of Certainty ratings (1=maybe, 2=probably, 3=certain) or change-of-mind/CoM (0=no-CoM, 1=CoM), in the lead-up to the initial-response (first and third rows) or the confidence-response (second and fourth rows). Columns show (A) Observed CPP and simulated absolute Decision Variables from the (B) Distinct-Boundary model and (C) Shared-Boundary Model.*

Conclusion

We replicated previous effects of post-decision speed-accuracy trade-offs on confidence ratings and extend them to a neural signature of evidence accumulation. Model fits greatly favoured Boundary-Based Stopping Rules over Time-Based ones, suggesting that post-decision accumulation may be governed by accumulation-to-bound, like the initial decision process. Validation against a neural signature of evidence accumulation distinguished between the similar Shared- and Distinct-process models, with the Shared-process Boundary model the only one able to account for effects of Certainty and CoM on the Decision Variable.

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