# An initial 'snapshot' of sensory information biases the likelihood and speed of subsequent changes of mind

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**Abstract**

We often need to rapidly change our mind about perceptual decisions in order to account for new information and correct mistakes. One fundamental, unresolved question is whether information processed prior to a decision being made ('pre-decisional information') has any influence on the likelihood and speed with which that decision is reversed. We investigated this using a luminance discrimination task in which participants indicated which of two flickering greyscale squares was brightest. Following an initial decision, the stimuli briefly remained on screen, and participants could change their response. Using psychophysical reverse correlation, we examined how moment-to-moment fluctuations in stimulus luminance affected participants' decisions. This revealed that the strength of even the very earliest (pre-decisional) evidence was associated with the likelihood and speed of later changes of mind. To account for this effect, we propose an extended diffusion model in which an initial 'snapshot' of sensory information biases ongoing evidence accumulation.

## Introduction

The ability to rapidly revise decisions in the face of new information is critical for avoiding harm in an ever-changing world. For example, imagine being unable to overrule a decision to run across a street when you realise that a speeding car is approaching. In situations such as this, even small delays in the time it takes to change your mind can have serious consequences. Given this, it is important to understand the cognitive processes which underlie rapid decision reversals, and the factors which influence the likelihood and speed with which they occur.

There is extensive evidence that perceptual decisions are made via the noisy accumulation of sensory information over time [1,2]. Once a certain amount of evidence has been accumulated in favor of one choice over another, an initial decision is made. However, following this the decision process does not immediately halt. Instead, sensory evidence continues to be accumulated, and, if enough subsequent evidence is accumulated in favor of the initially-unchosen response, a change of mind occurs [3].

Relative to the point at which an initial decision is made, two broad time periods can be defined: 1) a pre-decisional period, in which sensory evidence is being accumulated but a decision is yet to be reached, and 2) a post-decisional period in which a decision has been made but the evidence accumulation process is continuing to unfold. When considering these two time periods, one fundamental question which arises is whether information processed in the pre-decisional period ('pre-decisional evidence') has any influence on the likelihood and speed with which a change of mind subsequently occurs. Intuitively, it is appealing to think that pre-decisional evidence will affect subsequent change-of-mind behaviour. For example, if a decision is made on the basis of strong sensory evidence then it is reasonable to assume that this decision will be less likely to be overruled, or, if it is overruled, it will take longer for this to occur. However, it is also possible that change-of-mind decisions are be based solely on information processed after an initial decision has been made. Indeed, the most prominent model of perceptual changes of mind, the extended diffusion decision model [3], makes just this prediction. In particular, this model proposes that (controlling for decision accuracy) the decision process is in exactly the same state at the time of the initial decision, meaning that only post-decisional evidence influences change-of-mind speed and likelihood. It is therefore important to test between these two possibilities, to better understand how we rapidly change our minds about perceptual decisions.

Previous studies that investigated how people make discrimination judgements about dynamic stimuli (e.g., random dot motion stimuli or flickering dot arrays) have shown that, in trials where people change their mind, the sensory evidence provided by the stimulus initially favors one decision. However, just prior to the behavioral response being enacted, the evidence switches to favoring the alternative option, driving the change of mind [3–5]. It has been argued that, when controlling for initial response accuracy, the likelihood of a change of mind occurring depends on how strongly the initial decision was supported by the pre-decisional evidence [4]. However, in the study which purported to show this, sensory and motoric delays were not accounted for. Because it takes time for the brain to process incoming sensory information and output a motor response, decisions are actually made on the basis of information which was presented some hundreds of milliseconds earlier in time, and behavioural responses lag behind decisions by ~80 ms [3]. Since these delays were not accounted for, it is unclear whether the reported association was driven by truly pre-decisional evidence, or rather evidence which was presented prior to a behavioural response being made, but after the point at which it could have influenced the initial decision. Beyond the question of whether pre-decisional information affects change of mind likelihood, the

associated question of whether this information influences more detailed response characteristics, such as change-of-mind speed, has also not been explored. Understanding the influence of pre-decisional information on the speed with which decisions are overruled is important because the timing of decisions often offers a rich source of information about the underlying decision process [e.g., 6].

In previous studies of change-of-mind behaviour, random dot motion tasks have most often been employed [3,5,7,8]. To examine information usage in these tasks motion energy filtering [9] is required, leading to a smearing of information across time that prohibits the examination of early information usage due to a 50-150 ms lag in filter build up. To sidestep these issues, we employed a dynamic luminance discrimination task in which it is possible to examine information usage independently on a frame-by-frame basis, without filtering. To allow for fine-grained estimation of the participants' sensory information usage patterns (their 'psychophysical kernels'), we employed a small-N design in which each participant (n = 4) completed a very large number of trials [10]. Participants indicated which of two flickering grey squares was the brightest by pressing one of two response keys. After an initial judgment, the stimuli remained on screen for a brief period (1.5 seconds), and the participants were free to change their response. Critically, with each screen refresh (i.e. every 13.33 ms) a random luminance value was added to the mean luminance value of each square. Using psychophysical reverse correlation [11,12] we then retrospectively examined the impact that this residual evidence had on participants' decisions, on a frame-by-frame basis. If the luminance fluctuations at each frame are averaged across all trials they will cancel to zero, due to the fact that they are randomly distributed with a mean of zero. However, if the fluctuations systematically affect participants' decisions, then averaging across trials with shared decision outcomes (e.g., averaging over correct responses) will reveal when and how the fluctuations influenced participants' decisions across the pre-decisional and post-decisional time periods [see 15]. Below, we first describe the psychophysical kernels that this reverse correlation analysis revealed. Then, we account for these with a variant of the extended diffusion decision model.

## Results

Participants' changed their mind on 23.91% of trials (18.53% corrected errors and 5.38% spoilt responses) with an average initial response accuracy of 66.95% (80.10% of final responses were correct). To investigate whether pre-decisional evidence affected change of mind likelihood we sorted trials into four possible types: correct and error responses that were not followed by a change of mind, and correct and error responses that were followed by a change of mind (termed 'spoilt correct' responses and 'corrected error' responses, respectively). We then time-locked the residual evidence relative to: 1) stimulus presentation, 2) the initial response, and 3) the change of mind response, and averaged across trials within each response type (Fig. 1 A-C). This revealed clear patterns in the luminance residuals for change of mind trials. Evidence in early time windows favoured the initial response, whilst evidence in later time windows favoured the final response, replicating previous findings [3–5]. Strikingly, this also revealed that the strength of evidence favoring the initial response, for even the very first frame of evidence presented, differed depending on whether or not participants ultimately changed their mind (Fig. 1 A). To formally examine this effect, we fit a generalized linear mixed effects model to predict the probability of a change of mind occurring. This revealed a significant interaction between initial decision accuracy and the strength of the first frame of evidence on the probability of a change of mind occurring

(likelihood ratio test, $\chi^2$ (1) = 42.08, $p < 8.75 \times 10^{-11}$, see Supplement 1). This indicates that when the very first frame of evidence strongly supported participants' initial decisions, then changes of mind were less likely to occur. Note, here we have restricted our analyses to just the initial frame of evidence, as a pre-decisional evidence source. However associations between stimulus evidence strength and decision behaviour were by no means restricted to just the first frame. For illustrative purposes, we therefore also plot the results of frame-by-frame t-tests to compare differences in residual evidence throughout the trial (see Fig 1.)

Having found that the strength of the very first frame of evidence was associated with change-of-mind likelihood, we then investigated whether the strength of this information was associated with the speed with which changes of mind occurred. Plotting the residual stimulus fluctuations for fast and slow corrected errors and fast and slow spoilt responses revealed that changes of mind occurred more slowly after the initial response when the first frame of evidence strongly supported the initial decision (Fig. 1 D-F). To formally test this effect, we fit a linear mixed effects model to predict the speed with which changes of mind occurred. This revealed a significant interaction between initial decision accuracy and evidence strength on change-of-mind speed (likelihood ratio test, $\chi^2$ (1) = 4.27, $p$ = .039, see Supplement 1). This indicates that changes of mind were slower when the very first frame of evidence strongly supported participants' initial decisions.

Overall, these analyses demonstrate that the likelihood and speed with which participants changed their mind was already associated with the strength of even the very first frame of sensory evidence they saw (i.e. a pre-decisional source of information). These effects were consistent on the individual level (reported in Supplement 2).

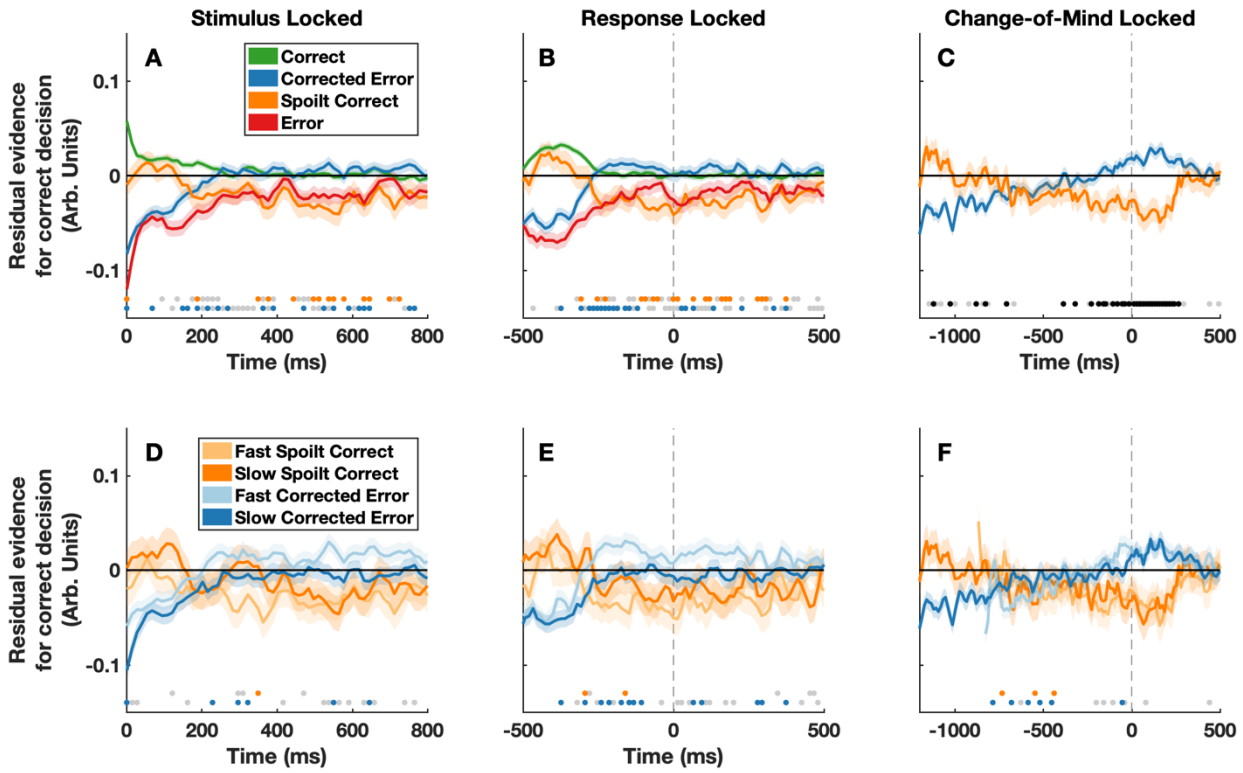


**Fig 1. Psychophysical reverse correlation results.** Panels A) and D) show the residual stimulus fluctuations time-locked to stimulus onset. Panel A) shows correct responses (green), error responses (red),

corrected errors (blue) and spoilt correct responses (orange). Panel D) shows fast (light blue) and slow (dark blue) corrected errors, and fast (light orange) and slow (dark orange) spoilt responses. Panels B and E show the same data, time-locked to the initial response (the time of the initial response is indicated by the grey dashed lines). Panels C and F show the data from trials containing a change of mind, time-locked to the change-of-mind response (the time of the change-of-mind response is indicated by the grey dashed lines). In all panels positive values on the y-axis indicate more evidence supporting the correct response. For display purposes a moving average smoothing function with a span of 3 frames was applied and a median split for change-of-mind response time was used in panels D-F. However, statistical analyses were conducted on the unsmoothed, continuous data. For illustrative purposes, t-tests (alpha level of .01) were also conducted to compare the residual evidence across specific trial types, at each frame. Orange dots denote timepoints at which there was a significant difference between correct and spoilt correct trials (Panels A-B), or where there was a significant difference between fast and slow spoilt trials (Panels D-F). Blue dots denote timepoints at which there was a significant difference between error and corrected error trials (Panels A-B), or where there was a significant difference between fast and slow corrected error trials (Panels D-F). Finally, black dots (Panel C) denote significant differences between corrected errors and spoilt correct responses, and grey dots (all panels) denote time points at which there was a significant difference for an alpha level of .05.

## Computational modelling

Having found that the strength of even the very first frame of evidence was associated with the likelihood and speed of subsequent changes of mind, we then sought to account for this effect within a computational framework to provide a mechanistic account of our findings. To this end, we employed the most prominent model of change-of-mind behaviour, the extended diffusion decision model (extended DDM; [3]). In this model, decisions are made by noisily accumulating the relative evidence between the two choice options (i.e. the difference in luminance between the two squares) to a threshold level. Once an initial decision has been made, sensory evidence continues to be accumulated. If enough evidence is accumulated against the initial decision, such that a separate change-of-mind threshold is crossed, then a change of mind occurs.

### *The original extended DDM predicts an insensitivity to pre-decisional evidence*

In the original version of the extended DDM [3], the drift rate (i.e. the rate at which sensory evidence is accumulated over time) is assumed to be constant across trials of matched stimulus difficulty. As such, the only source of variability within the decision process is within-trial noise (i.e. moment-to-moment fluctuations in the decision process). Critically, this leads to the prediction that pre-decisional evidence will have no influence on change-of-mind behaviour, in direct contrast to the current findings (see Fig 3 D & H). This is because, when controlling for initial decision accuracy, the decision process in the extended DDM is always in the same state at the time of the initial decision (i.e. there is always the same amount of accumulated evidence). As such, change-of-mind decisions depend entirely on the quality of post-decisional. However, in the fields of cognitive and mathematical psychology it is typical to assume that the drift rate varies from trial to trial [see 9]. This enables the DDM to account for the relative timing of correct and error responses, and, as we will demonstrate below, under this assumption the extended DDM no longer predicts an insensitivity to pre-decisional information (see Fig 3).

### *A novel variant of the extended DDM*

To account for the current findings, we fit a variant of the extended DDM which included trial-to-trial variability in drift rate. In particular, we assumed that there are both external (stimulus-driven) and internal (endogenous) sources of across-trial drift rate variability. We assumed that the

external variability component is a function of the residual evidence in the first frame of each trial, which linearly decreases over time (i.e. a decaying 'snapshot' of initial evidence). This means that when initial sensory evidence strongly supports one decision over another, the drift rate is temporarily biased in favor of that decision. This is consistent with recent evidence suggesting that across-trial variability in drift rate is partly stimulus driven [see 9]. To model the effect of trial-wise differences in internal states (e.g., attention, motivation, and arousal), we included an internal drift-rate variability component which was combined in an additive fashion with the externally-driven component. Finally, we assumed that moment-to-moment variability in the decision process (i.e. within-trial variability) was driven by both moment-to-moment variability in the stimulus as well as endogenous variability. This allowed us to reverse correlate the simulated moment-to-moment variability in the stimulus with the model-predicted behaviour, to construct model-based psychophysical kernels, which could then be compared to the observed psychophysical kernels.

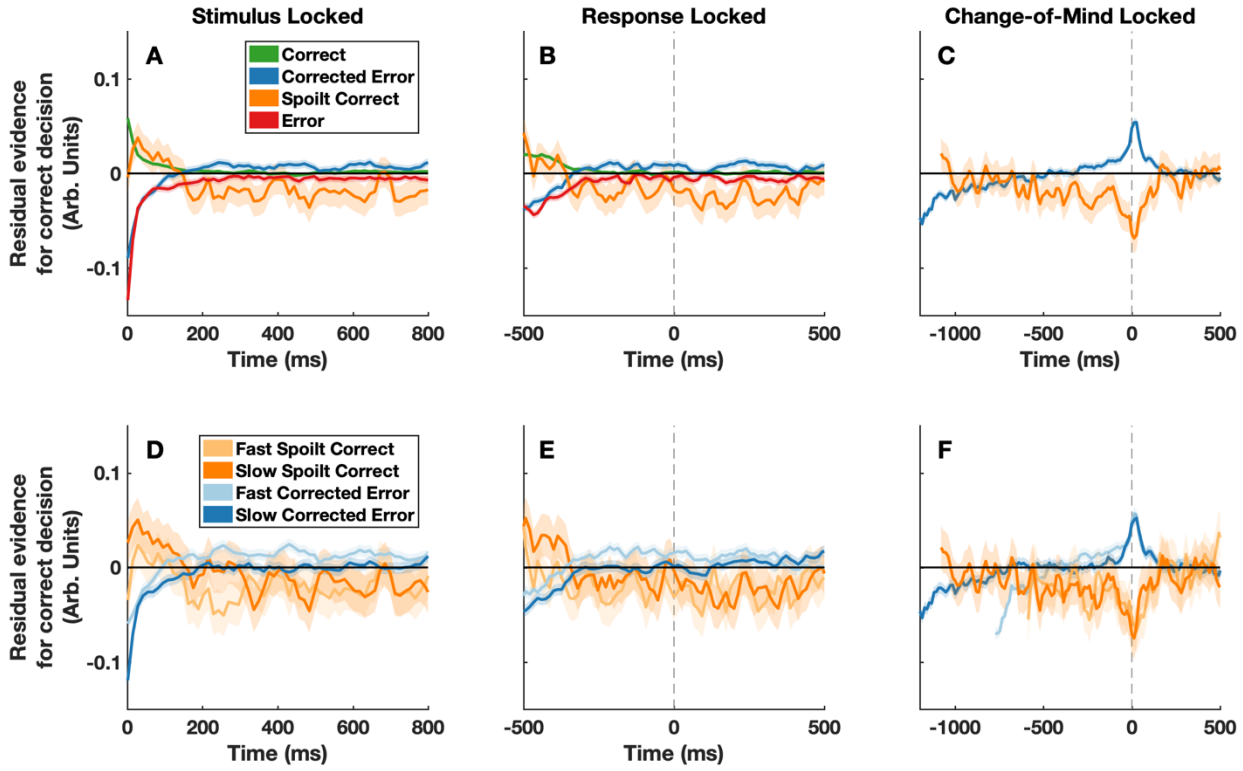


**Fig 2. Model-derived psychophysical kernels.** Panels A-F show the model predicted psychophysical kernels. To create these kernels we simulated decision variable trajectories in 100,000 experimental trials. We then took the within-trial noise in the model – used to simulate the moment-to-moment fluctuations in stimulus luminance – and reverse correlated this with the predicted response outcome on each trial. All plotting conventions are the same as in Fig 1.

We fit our variant of the extended DDM to the response proportions and response time quantiles for initial and change-of-mind decisions simultaneously (see Supplement 3). Strikingly, after being fit to just the behavioural responses, the model was able to predict the observed patterns in the psychophysical kernels (e.g., weaker initial evidence in favour of the initial response on change of mind trials; Fig 2). Importantly, when trial-to-trial drift rate variability was de-coupled from the first frame of evidence, but was otherwise identically distributed, the model was no longer able to capture the observed patterns in the psychophysical kernels (Fig 3 C & G). In this case, the

predicted pattern for the first frame was in the opposite direction to the observed results (i.e. stronger initial evidence in favor of the initial choice on change of mind trials). Finally, when there was no across-trial variability in drift rate the model predicted that there would be no differences in the psychophysical kernels for the first frame of evidence (Fig 3 D & H). By comparing these predictions, it is clear that stimulus-driven across-trial drift rate variability is the key feature within our variant of the extended DDM that allows it to capture the patterns in the psychophysical kernels. In simple terms, this indicates that the patterns we observed in the psychophysical kernels can be explained by an initial 'snapshot' of evidence exerting a slowly decaying bias on ongoing evidence accumulation.

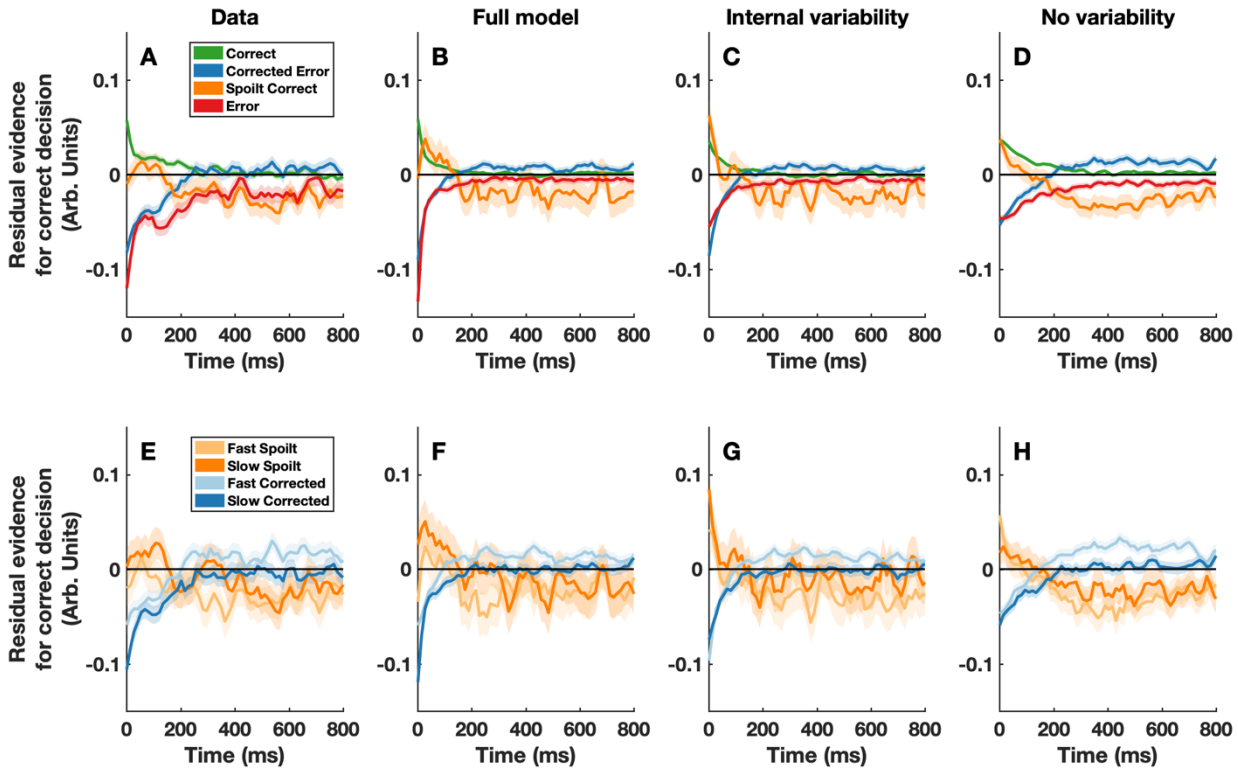


**Fig 3. Actual and predicted stimulus-locked psychophysical kernels.** Panels A and E depict the psychophysical kernels calculated from the data. To create panels B-C and F-G, we simulated 100,000 trials from three variants of the extended DDM model. The first variant (panels B and F) contained both external and internal sources of across-trial drift rate variability (same as in Fig 2). For the second variant (panels C and G) across-trial drift rate variability had exactly the same distribution, but was de-coupled from the stimulus (i.e. purely internal). Finally, for the third model variant (panels D and H) we simulated a version of the extended DDM in which drift rate was constant across trials. After simulating each model, we took the stimulus driven within-trial noise – used to simulate the moment-to-moment fluctuations in stimulus luminance – and reverse correlated this with the response outcome on each trial. All plotting conventions are the same as in Fig 1. See Supplement 4 for a plot of this data for the first frame only (i.e. at x = 0).

## Discussion

We investigated whether information processed prior to a perceptual decision being made ('pre-decisional information') influences the likelihood and speed of subsequent changes of mind. Participants made comparative luminance judgements between two flickering grey squares and indicated their decision with a button press. Following an initial decision, the stimuli remained on screen for a brief period and participants could change their mind. Using psychophysical reverse correlation, we examined the effects of moment-to-moment random fluctuations in luminance on

participants' decisions. We found that the likelihood and speed with which participants changed their mind was reliably associated with the strength of the very first frame of evidence they saw. To account for this observation, we developed a variant of the extended diffusion decision model (extended DDM), in which across-trial variability in drift rate is partially driven by the first frame of sensory evidence. Fitted to just the behavioural responses, this model was able to predict the observed patterns in the psychophysical kernels. Broadly put, this suggests that an 'initial snapshot' of sensory evidence exerts a slowly decaying bias on decision evidence accumulation, thus influencing later self-corrective behaviour.

The current study extends a nascent line of research examining the time-course of information processing underlying perceptual changes of mind [3–5]. One previous study has attempted to address the question of whether pre-decisional information affects change-of-mind behaviour [4]. However, because sensory and motoric delays were not accounted for, it was unclear whether the reported effect – a negative association between pre-decisional evidence strength and change-of-mind likelihood – was driven by evidence which was truly pre-decisional. Other studies investigating perceptual changes of mind have typically employed random dot motion tasks, making it impossible to examine the frame-by-frame processing of early sensory information in these experiments due the 50-150 ms lag induced by motion energy filtering. By employing a luminance discrimination task, we were able to circumvent this issue and present clear evidence that change-of-mind behaviour is affected by even the very earliest (pre-decisional) information one receives.

A novel variant of the extended DDM was able to recreate the patterns we observed in the psychophysical kernels, after being fit to just the behavioural response data [3]. In this model, trial-to-trial variability in drift rate is partly driven by a linearly decreasing function of the first frame of sensory evidence one receives (the fitted slope parameter causes this to decay over the course of ~1-1.5 seconds). This is consistent with the emerging view that a combination of both internal and external drift rate variability components is necessary to explain behaviour on perceptual decision tasks [14]. Comparing the predicted psychophysical kernels from our model to an otherwise identical model in which drift-rate variability is identically distributed, but de-coupled from the stimulus, it is clear that a coupling between the first frame of sensory evidence and drift-rate variability is the critical assumption for capturing the observed patterns in the psychophysical kernels.

We chose the extended DDM as a modelling framework because it is the most prominent model of change of mind behaviour, and because the parameters clearly link to different aspects of decision-making processes and are thus readily interpretable. However, there are other more complex – and arguably more biologically plausible – models which have been proposed to explain perceptual changes of mind [10,11]. Previous work has shown that under certain parameterisations of these models a 'primacy effect' occurs whereby early sensory information is weighted more heavily than later sensory information [13,17]. On face value this is similar to the bias exerted by the initial frame of evidence in the extended DDM variant in this study. Given this, it is possible that the initial evidence bias we have implemented in the current model, is in fact mimicking the primacy effect displayed by these more complex models. Future studies could examine the degree to which these models mimic one another, to uncover potential neural mechanisms through which initial sensory information might bias ongoing evidence accumulation.

One limitation of the current modelling approach is that, while our variant of the extended DDM was able to predict the weighting of the earliest frames of evidence (i.e. the experimental

effect of interest), it did not perfectly predict all observed patterns in the psychophysical kernels. For example, it predicted sharper peaks in the kernels around the time at which changes of mind occurred (compare Fig. 1 C & F to Fig. 2 C & F). This discrepancy may simply be due to the fact that the model was not directly fit to the psychophysical kernels. Alternatively, this may be a general limitation of the modelling framework or specific simplifying assumptions we adopted. For example, we assumed that the distributions of non-decision times for initial and change of mind responses were identical and were normally distributed. However, recent work has questioned whether alternative distributions of non-decision times might better explain behavioural data [18]. Future work could more exhaustively compare competing modelling frameworks and assumptions, to search for a complete account of these additional, as yet unaccounted for, patterns.

To conclude, we have shown that pre-decisional evidence does influence the likelihood and speed of perceptual change-of-mind decisions. In particular, we have shown that the strength of even the very first frame of evidence one receives is associated with the speed and likelihood of later decision reversals. Moreover, we have shown that this finding can be accounted for by an extended diffusion decision model, in which initial sensory evidence exerts a slowly decaying bias on the decision process. This suggests that an initial 'snapshot' of sensory evidence biases subsequent sensory evidence accumulation, thus influencing later self-corrective behaviour.

## Materials and Method

### Participants

Five people gave written informed consent and participated in the experiment. Participants had normal or corrected to normal vision and were aged 22–35 years (M = 26.4, SD = 5.32, 2 Female). Two participants were authors on this study (WT and DF). The others had pre-existing relationships with the authors, but were naïve as to the purpose of the experiment. Each participant completed 5 sessions of the experiment (except WT who complete 4.5 sessions due to a technical fault). Each participant was remunerated $15 AUD per session (except WT who did not receive payment). One participant was excluded from the final sample as they failed to respond in 19.44% of trials (the remaining participants only failed to respond in 1.9–3.1% of trials). The final sample was aged between 22–28 years (M = 24.25). The experimental procedure was approved by the University of Melbourne ethics committee (ID 1749951.1).

### Materials

All stimuli were presented on a Sony Trinitron Multiscan G420 CRT Monitor (Resolution 1280 x 1024 pixels; Frame Rate 75 Hz). Responses were recorded using a Tesoro Tizona Numpad (Polling Rate 1000 Hz). The task was coded in MATLAB 2015b using functions from the Psychophysics Toolbox Version 3.0.14 [19,20]. Whilst performing the experiment participants were seated in a dark room with their chin on a chinrest ~65cm from the screen.

### Procedure

In each experimental session, participants performed 1000 trials of a luminance discrimination task (Fig. 3). On each trial of the task they indicated which of two flickering greyscale squares (70 x 70 pixels; ~2.18 x 2.18 degrees of visual angle) was the brightest. The squares were presented side-by-side with 70 pixels separating them horizontally. Participants made their responses with their left and right index fingers on the 1 (left response) and 3 (right response) keys of the numpad. Participants had 800 ms from stimulus onset to make an initial response. From the time of the initial response, the stimuli remained on screen for a fixed duration of 1.5 s. During this time participants were free to change their response. Participants were told to try to be as accurate as possible in their initial responses and to correct any errors they felt they had made. At the end of each trial, feedback, corresponding to the final response participants had made ("correct", "error" or "too slow"), was presented for 300 ms. A red fixation dot was presented for 500 ms before stimulus presentation. Self-paced breaks were provided every 100 trials.

The mean RGB values for the brighter and dark squares were 142 and 130 respectively. On each frame, independent greyscale values for the two stimuli were drawn from separate Gaussian distributions centered around their respective mean values. The standard deviation of the distributions was 55 and the distributions were truncated at 1 standard deviation.

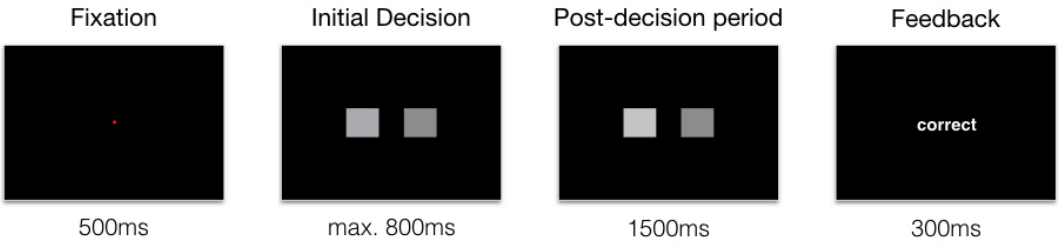


**Fig 4.** Schematic of the trial structure in the luminance judgement task. Each trial began with the presentation of a red fixation dot for 500 ms. The flickering stimuli were then presented, and participants were given up to 800 ms to respond. From the time of the initial response the post-decision period began, lasting for a fixed duration of 1.5 s. Feedback was then presented for 300 ms in the form of ('correct' or 'error'). If participants failed to respond within 800 ms of the stimuli being presented, the post-decision period was skipped and 'too slow' was presented for 300 ms.

**Psychophysical reverse correlation analysis**

With each screen refresh (i.e. every 13.33 ms) a random luminance value was added to the mean luminance of each square. This enabled the use psychophysical reverse correlation [11,12] to reveal participants 'psychophysical kernels' (their information usage patterns) across time. The logic behind this analysis is as follows: if the residual luminance fluctuations at each frame are averaged across all trials they will cancel to zero, because they are randomly distributed. However, if the fluctuations systematically affect participants' decisions, then averaging across trials with shared decision outcomes will reveal how, and when, the fluctuations influenced participants' decisions.

To calculate participants' psychophysical kernels, the frame-by-frame luminance values for the darker stimulus were subtracted from those of the brighter stimulus. The across-trial mean difference (i.e. the difference in mean luminance between the two squares) was then subtracted, and the residual luminance fluctuations were normalized between -1 and 1. These fluctuations were sorted into trials which shared a response outcome (e.g., purely correct) or response characteristic (e.g., fast corrected errors). When sorting the trials by change of mind speed we calculated median change-of-mind response times (relative to the time of the initial response) for each participant, within each testing session. After sorting by trial type, the fluctuations were pooled across participants and averaged (Fig 1). To obtain the results in Fig. S2, fluctuations for each trial type of interest were averaged within each participant.

**Statistical analyses**

Trials in which participants failed to respond (~2.6% of trials on average per session), or in which they changed their mind more than once (~3.2% of trials) were excluded from all analyse. Trials in which the change-of-mind response time was less than 50 ms were also excluded (~0.0004 % of trials). We also screened for trials in which the initial response time was less than 150 ms (no trials were rejected). Linear mixed effects models were used to analyse the data via the *lme4* [version 1.1; 20] package in R (version 3.5). A generalized linear mixed effects model was used to predict changes of mind, with main effects for initial decision accuracy and the first frame sensory evidence, as well as an interaction between initial decision accuracy and the first frame of sensory evidence. A linear mixed effects model was used to predict the time at which a change of mind occurred relative to the initial response (i.e. change of mind speed) with main effects for initial decision accuracy and the first frame sensory evidence, as well as an interaction between initial

decision accuracy and the first frame of sensory evidence. Likelihood ratio tests were used to formally examine the effects of interest (i.e. the interaction between initial evidence and initial accuracy). The distribution of response times for changes of mind was more normally distributed that typical initial RT distributions. We therefore analysed these responses with a linear mixed effects model. In all models, a random intercept for participant was included. Code to reproduce all of these analyses is available at https://osf.io/a6u4n/.

**Computational modeling**

We fit a variant of the extended DDM [3] to the response proportions and response time quantiles (0.1 0.3 0.5 0.7 0.9) of both the initial responses and the change of mind responses simultaneously. We simulated a discrete approximation of the extended DMM model (500,000 trials per iteration) and used the fminsearch algorithm (MATLAB 2016a) to minimize the root mean squared error between the simulated data and the actual data. Code for this model is available at https://osf.io/a6u4n/.

In our variant of the extended DDM, sensory evidence is noisily accumulated between two decision boundaries (0 and $B$). The average starting point of the accumulation process is half-way between the decision thresholds (i.e. $B/2$). From trial-to-trial the starting point varies uniformly around this average with a range of $Sz$. Once an initial decision threshold is reached, the evidence accumulation process continues to unfold. Note, that as in the original version of the extended DDM, there was a time limit parameter *timeOut* which specified the proportion of the post-decisional period for which participants processed additional information. If, during this period, enough evidence is accumulated against the initial decision such that a change-of-mind threshold – at distance of $B_{CoM}$ away from the initial decision threshold – is crossed, then a change of mind occurs.

With each timestep, the decision variable is updated as follows:

$$\Delta DV = drift * stepsize + noise * \sqrt{stepsize}$$

where, *drift* denotes the drift rate at a given time point, *noise* denotes the within trial noise at a given time point, and *stepsize* denotes the magnitude of the simulated timesteps within the model (0.001 s).

The drift rate at a given timepoint was determined as follows:

$$drift = mu + externalVar(t) + internalVar$$

where, *mu* denotes the mean drift rate, *externalVar* is the externally driven drift rate variability component at a given time point (this varies across time, see below), and *internalVar* is the internally driven across-trial drift rate variability component (which is constant across time). The externally driven across-trial drift rate variability component was determined as follows:

$$externalVar = -slope * t + s * firstFrame$$

Where, *slope* specifies the slope of a linearly decreasing function across $t$ (time within a trial), $s$ is a scaling parameter which is used to weight the internal representation of the first frame of sensory evidence (*firstFrame;* see below for details as to how sensory evidence is specified in this

model). The internally driven across-trial drift rate variability parameter (*internalVar*) is a normally distributed random variable with a mean of zero and a standard deviation *eta*.

At each time-step the trial-specific drift rate is affected by within-trial noise. This can be thought of as a noisy representation of the stimulus flicker, which is determined as follows:

$$noise = stimulusNoise + N(0, 0.1)$$

where, *stimulusNoise* is a normally distributed random variable with a mean of zero and a standard deviation of *theta*. Like the luminance fluctuations in the real experiment, the stimulus noise in the model was truncated at 1 standard deviation. Conceptually, the *stimulusNoise* parameter models the frame-by-frame fluctuations in stimulus evidence which influence participants' decisions (see Fig. 1).

Endogenous within-trial noise was modelled as a normally distributed random variable with a mean of zero and a standard deviation of 0.1. The standard deviation was fixed to 0.1 to act as a scaling parameter. Conceptually, this noise term accounts for within-trial sources of noise which were not stimulus driven (e.g., variability in moment to moment neural firing).

When determining the response times for initial responses and change-of-mind responses, we made the simplifying assumption that the non-decision time *tnd* and non-decision time variability *tndVar* components were the same for the two types of responses.

**Model-based psychophysical reverse correlation analysis**

To understand the effects of pre-decisional evidence on participants' behaviour, it was important to derive model-predicted kernels, which could be compared with the participants' actual psychophysical kernels. By comparing these kernels, it was possible to test whether our new model variant was using 'sensory' evidence in the same way as the participants.

To construct model-predicted psychophysical kernels, we simulated 100,000 experimental trials from each model of interest. Critically, each model contained simulated stimulus noise (see section on *stimulusNoise* above), representing the moment-to-moment fluctuations in stimulus evidence that participants saw. After simulating, we sorted the trials into the four possible response outcome types, based on the model-predicted response. We then took the simulated stimulus noise for each trial and time-locked this to stimulus onset, the initial response, and the change of mind. Finally, we then averaged this noise across trials with shared decision outcomes, yielding the model-based psychophysical kernel estimates.

**Data Availability**

Data are available at https://osf.io/a6u4n/.

**Code Availability**

Code for fitting the models and reproducing the statistical analyses are available at https://osf.io/a6u4n/.

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## Author Contributions

W.T., S.B., D.F., and R.H. contributed to conception and design. W.T. programmed the experiment, analysed data, and developed the modelling code. W.T. drafted the article and all authors reviewed and revised the manuscript. S.B. and R.H. funded and supervised the project.

## Competing Interests

We have no competing interests.

Supplement 1

Marginal effects from the two mixed effects models are shown in Fig S1. The parameter estimates from these models are shown in Table S1.

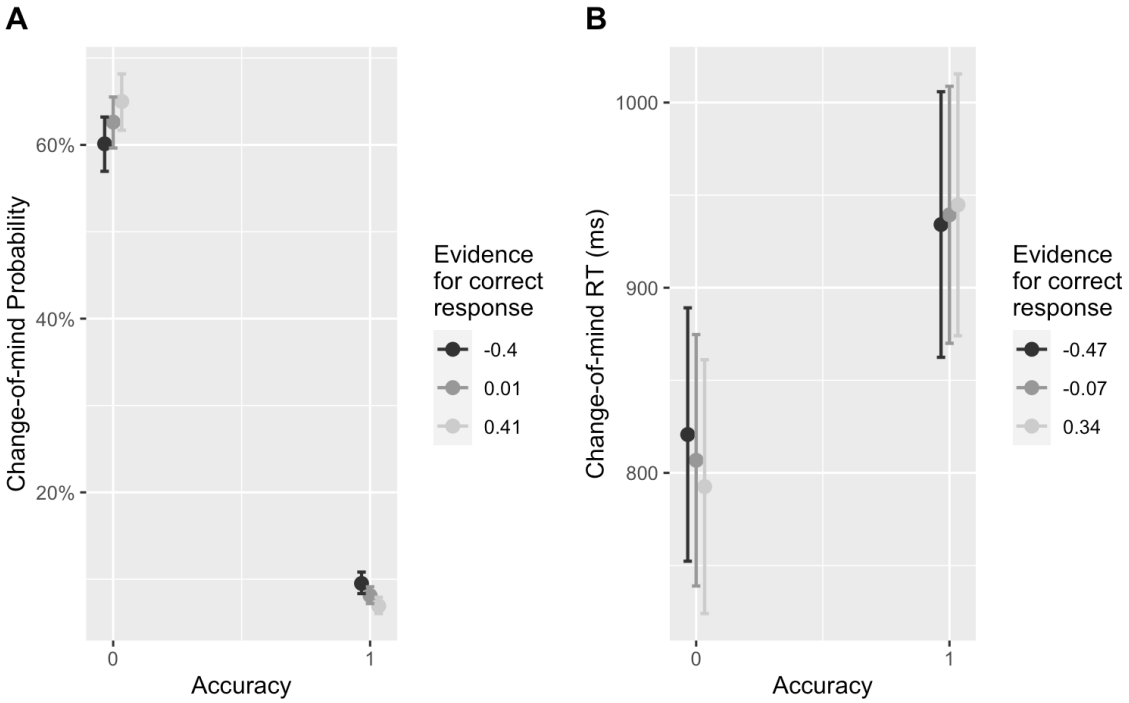


**Fig S1.** Predicted marginal effects for the interaction between initial decision accuracy and the strength of the first frame of evidence. Panel A) shows the marginal effects from a generalised linear mixed effects model predicting whether or not a change of mind will occur. Panel B) shows the marginal effects from a linear mixed effects model predicting change of mind speed.

**Table S1.** Mixed-effects models estimates

| | Change-of-mind likelihood model | | | Change-of-mind RT model | | |
|---|---|---|---|---|---|---|
| Predictors | Odds Ratios | CI | *p* | Estimates | CI | *p* |
| (Intercept) | 1.67 | 1.47 – 1.90 | **<.001** | 804.40 | 736.48 – 872.31 | **<.001** |
| Accuracy(1) | 0.05 | 0.05 – 0.06 | **<.001** | 135.90 | 116.90 – 154.90 | **<.001** |
| Evidence | 1.29 | 1.13 – 1.48 | **<.001** | -34.73 | -56.82 – -12.64 | **.002** |
| Accuracy*Evidence | 0.50 | 0.41 – 0.62 | **<.001** | 47.85 | 2.54 – 93.16 | **.038** |

Supplement 2

To check that the main findings were consistent on the individual level, we plotted the reverse correlation results, separately for each participant (Fig. S2). In line with the results above, we found that there was generally weaker evidence favouring the initial decision on spoilt correct trials, compared to purely correct trials (for 3/4 participants; Fig. S2I). For all participants we found that there was weaker evidence supporting their initial decision on corrected error trials, compared to purely incorrect trials (Fig. S2J). Similarly, for all participants there was weaker evidence supporting the initial decision for fast compared to slow corrected errors (Fig. S2K). Finally, for 3/4 participants there was weaker evidence supporting the initial decision for fast compared to slow spoilt responses (Fig S2J). Note that these trials were very rare (2.5% of trials for p1, 4.4% of trials for p2, 7.1% of trials for p3, and 7.5% of trials for p4), hence why there is more variability across participants.

Overall, these analyses further demonstrate that the speed and likelihood of changes of mind are associated with the degree to which the first frame of presented evidence supports participants' consequent decisions.

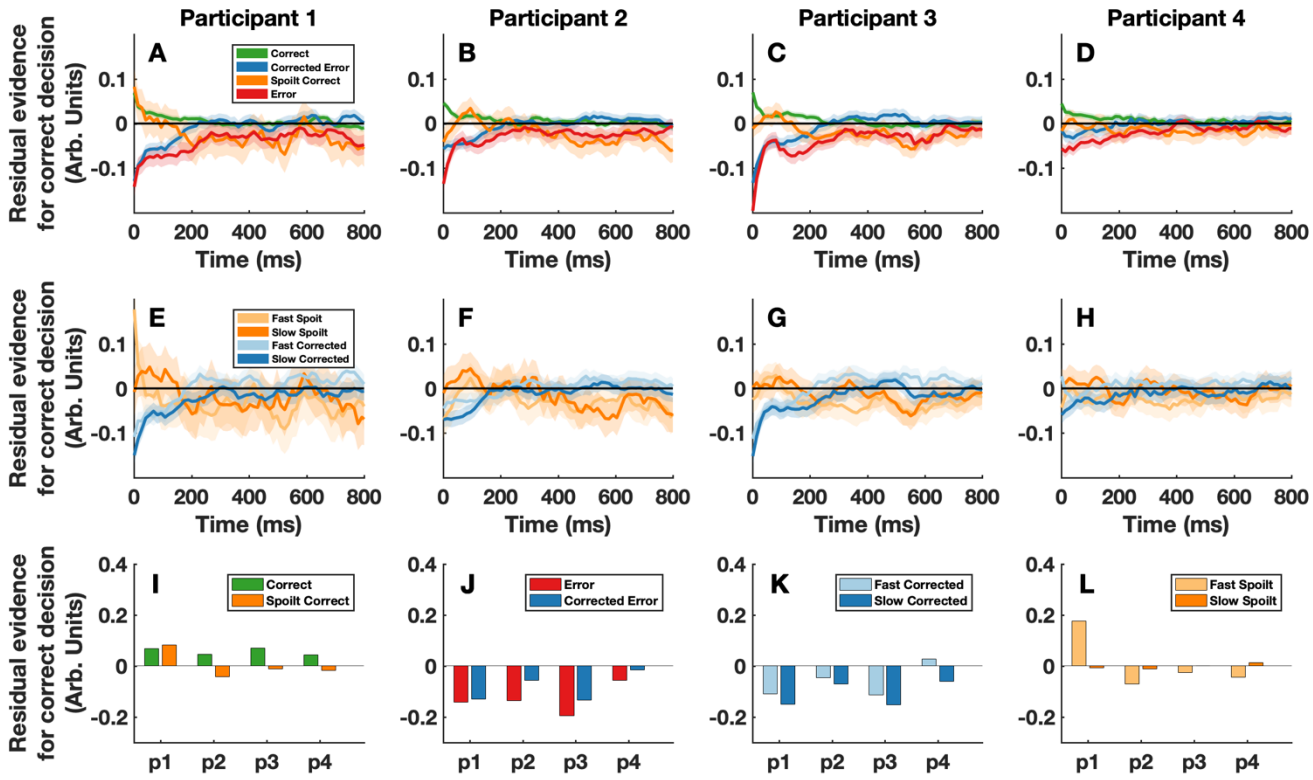


**Fig S2. Participant-level results.** Panels A-H show the stimulus locked psychophysical kernels for each individual participant. For display purposes a moving average smoothing function with a span of 3 frames was applied. Panels I-L show the average luminance of the first frame of evidence that participants were presented with (i.e. the data for x = 0 in Panels A-H). Panel I compares correct and spoilt correct responses, panel J compares error and corrected error responses, panel K compares fast and slow corrected responses, and panel L compares fast and slow spoilt responses. In these panels, participants are represented on the x-axis.

# Supplement 3

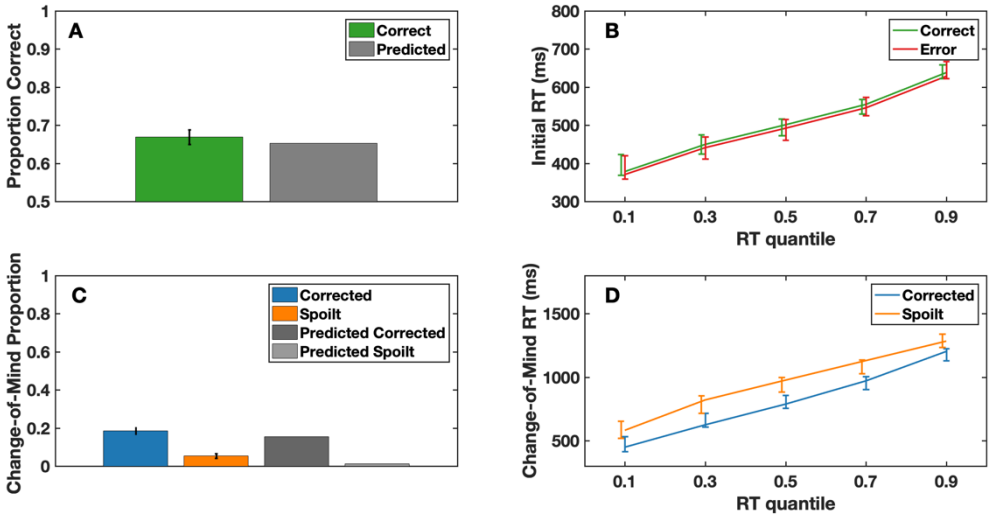


**Fig S3. Behavioural responses and model predictions.** Panels A-D show the behavioural predictions from the model, alongside the actual data. In panels B and D, the error bars represent the 95% confidence intervals around the mean of the experimental data, whilst the lines represent the predictions from the model. In panels A and C the black error bars represent the 95% confidence interval around the mean of the experimental data, and the grey bars denote the model predictions.

**Table S1.** Parameter estimates for the full variant of the extended diffusion decision model. *B* is the initial decision threshold, *Sz* is the range of the starting point variability, *tnd* is the non-decision time component for initial decisions, *tndVar* is the variability in the non-decision time component for initial decisions, *mu* is the mean drift rate, *theta* is the stimulus-driven within trials noise component used to model the fluctuations in the stimulus, *eta* is the endogenous across-trial drift rate variability component, *s* is the scaling parameter used to scale the internal representation of the first frame of evidence into the externally driven drift rate variability component, $B_{CoM}$ is the distance of the change of mind threshold from the initial decision threshold, *timeOut* determines that amount of post-decisional evidence that is considered (as a proportion of the total available time), and the *slope* parameter determines the rate at which the initial evidence bias decays.

| *B* | *Sz* | *tnd* | *tndVar* | *mu* | *theta* | *eta* | *s* | $B_{CoM}$ | *timeOut* | *slope* |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.153 | 0.150 | 0.445 | 0.842 | 0.461 | 0.449 | 0.370 | 0.357 | 0.568 | 0.903 | 0.0001 |

Supplement 4

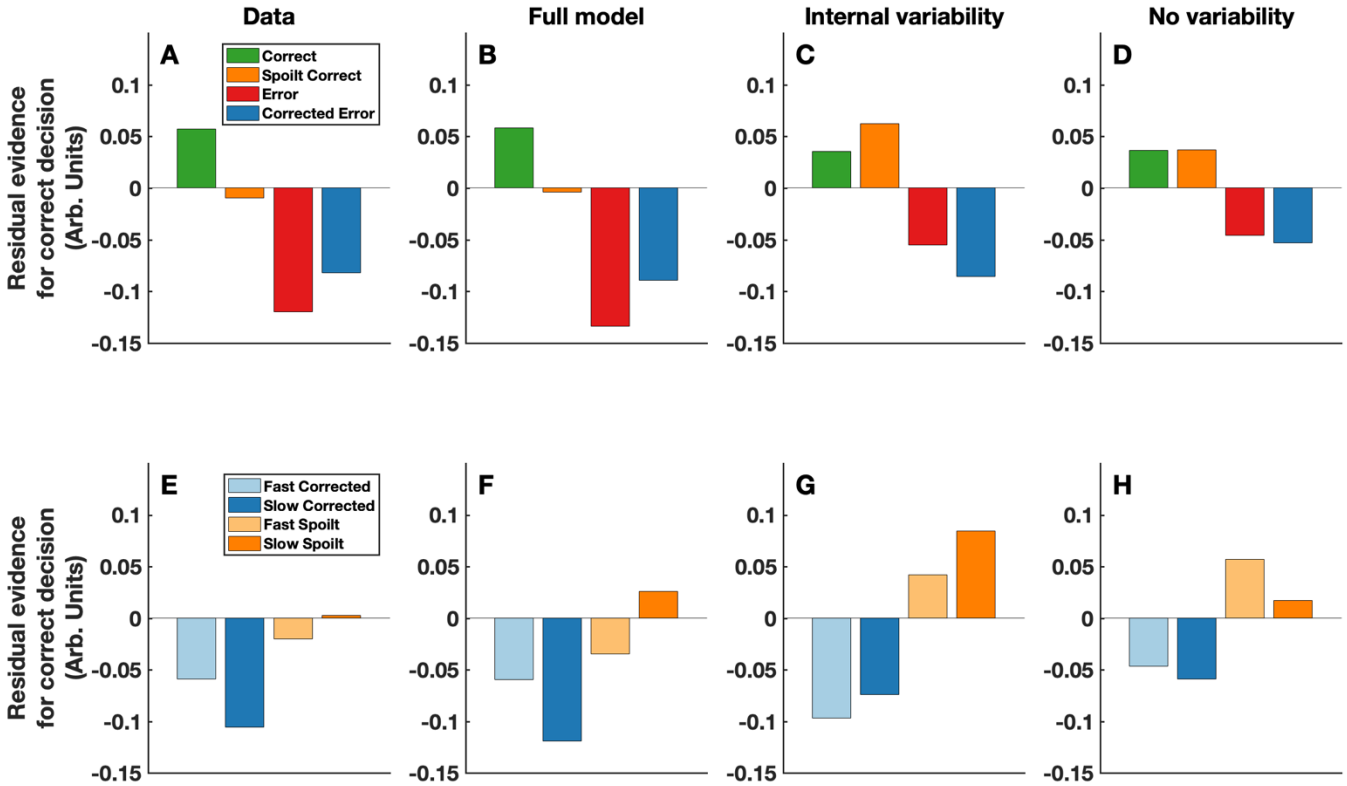


**Fig S4. Reverse correlation results for the first frame of evidence.** This figure displays the data from Fig. 3, for x = 0 only (i.e. for the very first frame of evidence). It is clear from this figure that a combination of externally and internally determined, across-trial drift rate variability is needed to capture the weighting initial evidence across response types.