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Dear Dr Marieke Schiffer and the Editorial Board at *Communications Psychology*,

Please find our revised submission of “Biased expectations about future choice options predict sequential economic decisions” by van de Wouw, McKay & Furl, originally submitted as COMMSPSYCHOL-22-0014 under the title "How we model prior belief is crucial for predicting decision biases in realistic contexts". This letter encloses details about how we feel our revisions have enhanced the scientific contribution of this work. And below that, we also include the new abstract and our point-by-point responses to the editor’s comments, which were included alongside the reviewers’ comments.

Our initial submission focused on how undersampling biases in realistic sequential decision problems (described in the Abstract) could best be compared to an ideal observer optimality standard, with a focus on how specification of this ideal observer’s prior over prospective option values changes the appearance of the bias. The editor and both reviewers felt the manuscript would be enhanced if it offered computational models as theories of undersampling bias, rather than focusing only on comparisons to optimality. We were also asked to run additional studies to further probe our participants’ apparent reluctance to change their sampling rates from condition to condition.

We have accomplished both goals, though they entailed large changes to the manuscript. We propose and build new computational models of biased sequential searches, validate them with parameter recovery, fit them to human participant data and compare their model fits. We apologise that the creation of this extra research output has taken the time that it has. Nevertheless, we now offer a paper that, as requested, is driven more by computational theory, that now directly explains participants’ undersampling bias and that cements and validates our empirical approach. We believe that the manuscript therefore now makes a stronger scientific contribution that is more appropriate to *Communications Psychology*. Many thanks to you and the reviewers for encouraging this more ambitious version of the work. We look forward to getting feedback on these changes from the reviewers, as we suspect they are what was being envisioned.

In brief (See Abstract for more detail), the main contribution now is that we show that it is the participants themselves who are mis-specifying their prior distribution over options. In doing so, participants derive from their mis-specified prior distribution suboptimally pessimistic expectations of future option values, thereby demotivating them from continuing to search and encouraging them to undersample. Optimality ideal observer models, which are not subject to this bias, are freer to increase their sampling rates when it is adaptive to do so: Such as for incentivisation schemes that favour more option sampling and when sequences of options are longer. The new manuscript demonstrates increased undersampling bias in both these scenarios.

Sincerely,

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Abstract

Considerable research has shown that people make biased decisions in “optimal stopping problems”, where options are encountered sequentially, and there is no opportunity to recall rejected options or to know upcoming options in advance (e.g., when flat hunting or choosing a spouse). Here, we use computational modelling to identify the mechanisms that best explain decision bias in the context of an especially realistic version of this problem: the full-information problem. After eliminating a number of manipulations as potential instigators of bias, we examined two manipulations where an optimality model recommends sampling more options before deciding – sequence length and payoff scheme. Here, participants were more reluctant than was optimal to increase their sampling rates, leading to undersampling bias. Our comparison of several computational models of bias demonstrates that participants maintain these relatively low sampling rates because of suboptimally pessimistic expectations about the quality of future options (i.e., a mis-specified prior distribution). These results evidence a new theory about how humans solve full information problems. Understanding the causes of decision errors could enhance how we conduct real world sequential searches for options, for example how online shopping or dating applications present options to users.

Below we address point by point the editor’s comments.  
  
  
*Editorially, we consider three aspects key: the evidence put forward in support of your interpretation must be strengthened through additional empirical data and further analyses, the key advance must be demonstrated more convincingly and explained more clearly and the use of appropriate statistics and improved statistics reporting is required. Please note that the editorial requests incorporate advice we received from Reviewer #2 in an additional email exchange in which we enquired about ways to address their key criticism as listed below.*

We were asked to provide new empirical data by Reviewer 2 and a theoretical model comparison by both reviewers. Having done this, we think the new manuscript now more clearly addresses these three aspects. We have indeed collected and now report two studies worth of new data and we have built original theoretical computational models and fitted and compared these models to behaviour. The key advance reported by the new manuscript asserts that undersampling bias is susceptible to payoff scheme and sequence length, in part because the optimality ideal observer model is more sensitive to these factors than participants are. We find that participants’ limited willingness to adjust their sampling rate (relative to that of the ideal observer) is explained (via computational modelling) by biased expectations / belief about the distribution of future option values (i.e., our biased prior model).

We thank the editor and reviewers for encouraging us to drill deeper in our data set and to bring in new data, as (in our opinion) we stand on more rigorous ground in the current report and believe the revised manuscript can make a more substantive contribution, especially in terms of theory.

*First, as Reviewer #2 highlights, it is presently not evident whether the absence of measurable change in behaviour is a result of manipulations that are genuinely without an effect, or a feature of the paradigm. You will need to conduct additional work that demonstrates that the task allows manipulation of human behaviour. This work should be preregistered and powered a priori to detect subtle effects.*

We have satisfied this request with new empirical data. Our pre-registered Study 3 shows that sequence length can significantly modulate participants’ sampling rate. This finding, in fact, is itself already a replication of Costa & Averbeck (2015), upon which our study’s design is principally based.

We also now report Bayesian tests of null models (the new Figure 2), which show sufficient sensitivity to detect positive statistical evidence that participants’ mean sampling rates are equal / null between conditions.

We note that our manipulations were sufficiently sensitive to detect differences in the sampling rate for the ideal observer models. We show, for example, we can detect an effect of incentivisation scheme on model sampling rate but not on participant sampling rate.

Lastly, we would like draw attention to the possibility that participants’ rigid sampling rates could indeed have always been the ground truth, even had we not been able to find another manipulation that successfully modulates participant sampling rates. We note that the reviewer text we received does not explicitly articulate what specific feature of our design must be preventing measurement of changes in participant sampling rate.

*Please also note Reviewer #1's critique regarding the effect of payoff schemes as you address this point.*

We agree with Reviewer 1 that the payoff / incentivisation scheme has important influence over the ideal observer’s sampling rates. Indeed, we now use this finding as an illustrative example of how participants are reluctant to raise their sampling rates under incentivisation schemes where the ideal observer suggests that it is optimal to do so.

*Second, as likewise mentioned by Reviewer #2, a key issue is clarifying and strengthening the insights that arise from the work. The effects demonstrated here arise from a comparison between computational models of human behaviour, with little insight into why human behaviour differs from the optimal solution; at a minimum, the goal of revision should be to convincingly demonstrate that commonly used implementations of the model produced results that are artificially interpreted as over/undersampling.*

We believe that our new model comparison provides this “insight into why human behaviour differs from the optimal solution”. We tested a number of theoretical computational models, each of which implemented a bias term that specifies how optimal performance might be systematically skewed. We fitted and compared these models in eleven conditions / datasets and obtained remarkably replicable results, which implicated prior expectations of option quality as the computational factor that leads to bias.

*Finally, Reviewer #1 provides a number of constructive suggestions for how additional analyses would strengthen the evidence and generate a more complete understanding of human behaviour in the task. We ask you to address these suggestions, and at the same time, provide Bayesian statistics or equivalence tests for all null-results, which can otherwise not be interpreted. You will find more information about our guidelines for statistics in the PS.*

Thanks to the editor and this reviewer for encouraging us to take a deeper look at our data. We now print the results of Bayesian pairwise tests on our plots throughout the manuscript.

However, it may be the Bayesian tests in the new Figure 2 that most directly address the reviewer’s concern. Here, we see that (except for the full condition, which uses a different payoff scheme), participants’ mean sampling rates were statistically equal (greater evidence for the null model) for all other pairwise tests between conditions. This provides positive evidence that none of the methods features we tested in these conditions changed participants’ sampling rates.