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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. Many thanks for the opportunity to revise in response to this second round of reviews. We were pleased to receive this largely positive response and constructive comments. Below we include our point by point response to the editor’s comments, with the point by point responses to reviewer comments re-submitted under separate cover.

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 the following points key:*

*Both reviewers request a qualitative evaluation of the model fit that demonstrates how well the model emulates human data.*

We have added text to the General Discussion (the bulk of which begins on line 696) to explicitly address this issue. We highlight the following points.

* Already in the top rows of the revised figures 3-7 we have reported the mean sampling rates and in the top rows of figures S7, S9-S11 and S14 the ranks of chosen options for all the models. We plot these alongside those of participants for direct comparison of whether the models can reproduce participants’ performance. All models well reproduce participants’ sampling rates and the Cost to Sample and Biased Prior models (but not the Cut Off heuristic) well reproduce participants’ mean rank of chosen option.
* Now, we have additionally leveraged the relatively large sample size in Study 3 to perform additional model validity tests and added these to the Supplementary materials. These analyses contribute to the evidence that all our models / heuristics well-predict and fit human data to some degree.
  + First, we respond directly to the first reviewer’s question *“How does the BP model's prediction of participant behavior differ from the CS model?”* and the second reviewer’s request to “*see how well the models recreate the data*“. Here, we supplied scatterplots and correlation coefficients in Figure S12 showing the relationships between sampling rates of the models versus those of individual participants. These plots strongly validate the Biased Prior model and the other models.
  + Second, we provide an analysis of decision threshold as a function of sequence position in Figure S13, using the Lee (2006) threshold-fitting method for both our human and model choices. Again, all the models perform similarly when predicting human performance.
* Our analyses of frequency of participants best fit by each model, shown in the bottom rows of figures 3-7, show that many participants in our samples may even be best fit by other models, especially by the Cost to Sample model.

The reviewers are not specific about which analyses they would like to see, aside from the requests we already quoted and responded to above. Of course, we would be happy to consider further validation analyses and agree that learning more about when prediction diverge is an interesting research question. Given the apparently subtle nature of these divergences, however, perhaps the issue of divergent predictions might be ideally addressed in separate research projects, using paradigms specifically designed to maximise dissociate performance. We have also taken up this consideration in our revised General Discussion.

*Second, the reviewers raise questions about the (cognitive) feasibility of the modelled processes.*

We have added some text addressing this issue in the General Discussion beginning line 794. Specifically, we point to the lack of certainty with respect to the capacities of the neural architectures that might be implementing these algorithms. And, more concretely, we cite evidence from previous fMRI studies showing that brain responses indeed correlate with quantities computed by backward-induction-based optimal stopping models.

As recommended by Reviewer 1, we have expanded the description of backwards induction, with additional text in the Supplementary Materials.

*Finally, they raise the question of the consequences of (non)optimal behaviour on the task.*

We address this issue in a new paragraph in the General Discussion beginning line 809.

Given we have systematically manipulated several methods here, it might appear that we have thoroughly explored the potential space of factors that affects the size of sampling biases. Nevertheless, in our view, we have not scratched the surface yet. Indeed, we show (like Costa and Averbeck did before us in 2016) that the undersampling bias grows with larger sequence lengths. We have examined only lengths of 10, 12 and 14 here. We expect that undersampling bias likely continues to grow at least to some degree. Moreover, less is known about the circumstances of real world searches. There are likely many parameters involved in real world searches, including longer sequence lengths, that we did not examine here in our relatively tightly controlled studies. Our view is that our findings can motivate new inquiries along these lines.

*The referees also highlight the potential for more model comparisons (additional models). While this may be interesting for future work, we ask you to not place an emphasis on this issue, and rather focus on the requests outlined above that will aid to demonstrate the characteristics and plausibility of the models currently applied.*

With respect to this proposal of new models, have focussed our response to new text in the General Discussion concerning the utility of the framework we have introduced here for modelling in future studies. We discuss the importance of models and heuristics that might be built and tested using this novel modelling framework, mentioning the specific examples proposed by the reviewer.