*Reviewer #1 (Remarks to the Author):*  
  
*I thank the authors for addressing my previous comments and for the considerable effort invested in revising the manuscript. In this revised version of the manuscript, the authors have added several theoretical models aimed at explaining the behavior of the participants. Generally, the addition of these models improved the manuscript. However, since the article has undergone considerable changes, I have a few additional comments regarding the new version of the manuscript, both in relation to its clarity and in relation to the newly added models.*

*• Clarity and presentation - The introduction and paradigm description remain relatively clear. However, the model description and results sections are relatively complex and less intuitive. I suggest several improvements:*

We appreciate the reviewer’s appreciation of the new modelling contributions! And we of course are pleased to implement these constructive comments to help improve clarity.

*o Ideal observer model - The basic model is explained in a relatively abstract way. A simple numerical example or visualization (e.g., one that illustrates the backwards induction) could help readers who are not familiar with this model to understand it better.*

We have added a section to the supplementary materials that takes the reader through an intuitive and more concrete step by step description of backwards induction.

*o Abbreviations - Throughout the article, the authors used abbreviations such as CO, CS, etc. Using the full names of the models could enhance readability and flow of the text.*

We now spell out these abbreviations.

*o A table summarizing the key features of each model could help.*

We have created a new Table 1 for this purpose.

*o Figure 1 - The font size is relatively small, making it difficult to see what is written.*

As these are screen shots of the actual paradigms, we are not able to change the font sizes without misrepresenting how the paradigm was presented. Therefore, we have reorganised the figure to enlarge the screen images to make the text more visible. This means individual paradigms cannot be separate panels. So we have created multiple figures, one for each paradigm, enlarged to full page size, in the supplementary materials. We have kept the baseline paradigm (previously panel A) as Figure 1 in the main text to keep one illustration of how a paradigm of this kind generally appears.

*o Figures 2-7 - i. Adding a legend explaining the color coding would assist in understanding the Figure more easily. ii. Some of the BIC values look almost identical, and it is very difficult to distinguish between them. Adding numerical BIC values would facilitate easier comparisons between the models. iii. Figure 3 - Column headings would make the figure clearer.*

We have added all these features to the figures.

*• Qualitative versus quantitative comparison - While the BP model's superior BIC values indicate a better fit, it would be helpful to understand the specific qualitative aspects of the data that contribute to this superiority. For example, how does the BP model's prediction of participant behavior differ from the CS model (i.e., both models predict under-sampling, so where are their prediction differ)? Providing a more detailed comparison of the predictions and behavior patterns could illuminate why the BP model outperforms others.*

The top rows of the revised figures 3-7 report 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. It can be seen that all models reasonably reproduce participants’ sampling rates and the Cost to Sample and Biased Prior models (but not the Cut Off heuristic) closely reproduce participants’ mean rank of chosen option.

We have added two new analyses, exploiting the large sample size in Study 2. In Figure S12, we report relationships between individual differences in participants’ versus models’ sampling rates. This analysis responds to the reviewer’s request to report “*how does the BP model's prediction of participant behavior differ from the CS model”.* We find that both Biased Prior and Cost to Sample models show robust correlations. In Figure S13, we also provide an analysis of participant and model choice thresholds. The reviewer has not specified what other “detailed comparisons” would be desired but we would be happy to consider other analyses.

We have also added to the General Discussion the important point that all the models appear to well predict participant behaviour and, in some cases, the Cost to Sample model also fits a remarkable portion of our samples (e.g., in Study 3). We suspect that where model predictions differ might be subtle and vary from participant to participant, and we recommend using paradigms that intentionally manipulate factors that should dissociate the models.

In our revised General Discussion beginning line 697 we address these issues:

“We should note, however, that the Cost to Sample model – in which participants perceive sampling itself to be costly or rewarding – was the best-fitting model for a substantial number of participants and therefore may explain suboptimal decisions in a subset of our participants. Indeed, all our models well-predicted participants’ mean sampling rates (Figures 3-7), participants’ mean rank of chosen options (Figures S7, S9-S11, S14), except for the Cut Off heuristic, which obtained much lower ranks than participants. Our supplementary analyses of the large sample in Study 2 show individual differences in participant sampling rates were well-predicted by all three models (Figure S12). And, participants’ sequence specific thresholds were approximated by all three models (Figure S11). The framework we promote here, therefore – using an ideal observer to model accurate performance and then parameterising it to account for systematic bias – appears to produce models that predict participant data with reasonable accuracy. Moreover, different participants in the same sample might adopt any of these strategies, even if the Biased Prior strategy might be the most common. In some cases (as in Study 3), the Cost to Sample model best fit a remarkable share of individual participants. Given the high predictivity of all our models, it can be difficult to discern exactly what choices the Biased Prior is superior at predicting, compared to other models. Our recommendation is that these models be compared on paradigms specifically designed to test this hypothesis. For example, manipulations of participants’ expectations about upcoming option values (i.e., their prior) should produce the types of systematically different decisions that would be predictable from a Biased Prior model.”

*• Additional model considerations - The models implemented provide valuable insights, but exploring additional models could yield even richer findings.  
o For example, did the authors examine a combined BP and CS model? Since the mechanisms underlying these two models are different, a combined model might be able to achieve better results.  
o Another possible model is one similar to BP/CS but assumes time-varying parameters (for example, that the sampling cost increases over time). This idea is similar to the urgency signal/collapsing boundaries in sequential sampling models.  
o The CS and BP models are essentially versions of the IO model. There may be models from different families that might explain the participants' undersampling. For example, a model that assumes that the participants scanned the space of possibilities partially (e.g., only for 3-4 levels), and therefore undersampled.  
o Exploring some of these models (or at least discussing them as potential avenues in the discussion section) could strengthen the manuscript.*

We agree with the reviewer that the introduction of the modelling framework in this paper opens many new avenues for theory development and we share enthusiasm for these possibilities. We have added text in our General Discussion outlining these interesting new research directions, as advised by the reviewer:

“We have introduced a framework whereby optimality solutions including that of the Secretary Problem and that of the full information problem have been leveraged to explain accurate performance on optimal stopping tasks. And our framework has taken the approach of parameterising these models to explain systematic sources of suboptimal performance. Given that we have proposed this framework and demonstrated its utility, we expect that future research can refine the models we have proposed or build improved models that may better fit participant data. For example, more complex models that combine multiple bias-related free parameters (e.g., the cost to sample parameter and a constant added to the prior mean as fitted parameters at the same time) might be considered. Also, more sophisticated versions of our models might be formulated, such as cost to samples that change across sequence position …. Future research might explore models that use a limited-capacity backwards induction, which can only partially explore possible future states, or use a simpler heuristic to approximate the choice threshold / value of sampling again.”

*• Model feasibility - In the context of the previous comment, the BP model outperformed the other models in terms of BIC results. However, the feasibility of the calculation required by it raises questions about its psychological plausibility. How realistic is it for participants to perform such complex calculations? Could simpler heuristics underlie what appears to be complex computation?*

We have added to the General Discussion some text addressing this issue, including citation of previous evidence from fMRI that neural responses may encode quantities computed by these kinds of models. We note also that we have already included in our model comparison a simpler heuristic (the cut off model) and the model fitting evidence appears to be against this heuristic and more in favour of the models based on the ideal observer.

We write in the General Discussion:

“When considering models that might be built and tested in the future, it is worth considering that the Bayesian ideal observer solution to the full information problem (which we used as a base for some of our models) is relatively computationally complex, especially its backwards induction algorithm (See Supplementary Materials for more information). Future research might explore models that use a limited-capacity backwards induction, which can only partially explore possible future states, or use a simpler heuristic to approximate the choice threshold / value of sampling again. Though we note that already our evidence here undermines the case for a previously proposed heuristic, the Cut Off heuristic. In any case, we do not know the capacity of the neural architectures involved in solving these problems, rendering it difficult to reject models a priori on this basis. Indeed, it is plausible that neurons may be implementing similar computations as the kinds of models we investigated here. It has already been shown that brain responses correlate trial-by-trial with fluctuations in quantities derived from backwards induction based optimal stopping models that have been fitted to human participant choice data (Costa & Averbeck, 2016; Furl & Averbeck, 2011).”  
  
• *Optimality - Given that human performance closely matched the optimal model in term of rewards, what are the practical implications of under-sampling? And whether, given a sampling strategy similar to that of the Bayesian model, the subjects would indeed achieve better results or reach a plateau?*

We have expanded on our existing text in the General Discussion regarding the comparison of ranks of chosen options between participants and the Ideal Observer.

“We have already mentioned several ways that the modelling framework we propose here and the results we have obtained raise new research questions and open new research lines. One last issue that we also feel deserves further study relates to the extent to which systematic bias translates into real losses for participants. We have already proposed above an interesting theoretical possibility that biases like Biased Prior strategies might have an adaptive function, so long as they produce near-optimal performance. Indeed, within the narrow range of sequence lengths and domains (i.e., smartphones prices) that we have examined here, participants’ biased choices largely satisficed, and produced performance that, while not optimal, did not cause a striking loss for participants, when measured as rank of chosen option. Nevertheless, we also show herein that factors such as sequence length and incentivisation can affect the size of bias (e.g., longer sequences increase undersampling bias, as the Ideal Observer adjusts to the longer sequences but participants less so). Just how large biases can eventually become and the extent to which significant losses might accrue for agents due to ever larger undersampling biases cannot be answered directly by our data and would benefit from more direct investigations. Ideally, future studies could better approximate real-world conditions of decision making, or even collect field data “from the wild”, to assess what kinds of losses might (or might not) occur under more ecologically valid conditions, as opposed to the more tightly controlled studies we report here.”

*• Minor comments  
o How did the researchers correct the comparisons for multiple corrections?*

We have clarified in the text that the corrections were Bonferroni.

*o There is a typo in line 548*

We have corrected this.

*o Lines 582-583 are different from what the figure shows.*

Thank you for identifying this typo. We have corrected “undersampling” to “oversampling”.  
  
  
  
*Reviewer #2 (Remarks to the Author):*  
*This revision is a substantial revision from the previous version. The new version addresses nearly all of the issues I raised in the last round:  
- providing evidence that their studies could shift sampling rate  
- using statistical inference methods that allow one to collect evidence in support of the null (i.e.,Bayes factors)  
- using models to get at a more mechanistic explanation  
  
The paper and research is well executed and I found the results on undersampling and explanation to be informative.*

We are pleased the revision addresses this reviewer’s concerns and for this positive response.

*One comment that would help give me more confidence is to see model fits to the actual data. How well do the models here recreate the behavior. I may have missed this, but the modeling results are relative model comparisons. It would be nice to see how well the models recreate the data.*

The upper panels of figures 3-7 show the sampling rates of the models and how they compare (favourably) to participants’ mean sampling rates, suggesting that they do reproduce the results. The Supplementary figures show the models’ mean ranks of chosen options alongside those of participants. With the exception of the Cut Off heuristic (which consistently and considerably undershoots participants’ performance), the other models perform similarly to participants.

We have now added scatterplots and correlation values (Figure S12), showing that sampling rates are also well-predicted by all models at the level of individual participants, using the relatively large sample size in Study 2. Also from Study 2, we report a new analysis of thresholds at different sequence positions in Figure S13.

We hope these collectively demonstrate the value of the Biased Prior model for predicting sampling choices in the majority of participants.