Full information problems are probably the most realistic optimal stopping scenarios, but concomitantly, they are probably also the most computationally challenging to solve. Indeed, many previous implementations of optimal stopping problems have intentionally removed one or more of the aforementioned features to render the problem simpler and more computationally tractable (Ferguson, 1989). To solve full information problems successfully, the agent must incorporate knowledge of option values, their generating distribution and the reward values of their choices to balance the potential of improving on the current option against the prospective risk of losing highly-rewarding options if too many options are sampled (Furl et al., 2019). Fortunately, algorithms that produce optimal solutions for full-information problems now exist (Costa & Averbeck, 2015; Gilbert & Mosteller, 1966). The behaviour of these optimality models, in the guise of an “ideal observer”, can be compared to human behaviour to detect bias.

As in Pilot baseline, both OV and SV versions of CS and CO best reproduce participants’ sampling rates (Figure three, top right), although CO fails to reproduce participants’ performance in terms of ranks achieved (Figure S4 in Supplementary Materials). Moreover, individual participant sampling rates simulated by the fitted CS OV and CS SV models better predict participants’ empirical sampling rates better than any other model (Figure S5 in Supplementary Materials). Model comparison using BIC scores (Figure 3, middle right) suggested that the OV and SV versions of both CO and CS produced better average model fits than other models, while differing little from each other. However, when considering the frequency of participants that best-fitted each model (right panel in the third row of Figure 3), CS SV was the best-fitting for more participants than any other model. However, both CO models (CO OV and CO SV in sum) fit approximately as many participants as both CS models together. It is thus possible that some participants in this sample used a CO heuristic, although this model seems less adept at accurately predict participant samples and ranks than the CS model. To disentangle CO and CS contributions to the full condition, we will test replications of this full condition in Studies 1, 2 and 3. To foreshadow these reports here, these studies will agree that the CS model is most predictive of participants’ decisions, while CO models show some irregularities in this regard.

In summary, the optimality IO model sampled more for Pilot baseline than for Pilot full, leading to evidence for undersampling in Pilot baseline but no evidence for undersampling in Pilot full. As the difference in participants’ sampling between Pilot baseline and Pilot full was relatively small, and the difference with OV and SV versions of IO was relatively small, the different biases in the two pilot studies presumably arose due to the differences in their reward payoffs. Both studies showed some evidence that the theoretical CS model well-fit participants’ choices.

In summary, our hypotheses about the effects of methods features were largely confirmed. Participants sampled roughly the same amount across conditions, regardless of methods features. The IO models were not sensitive to most of the methods details either. Indeed, they are not even programmed with information about whether there are grey squares, etc. and so could not have shown such effects. However, the IO model is programmed with the payoff scheme and duly appears to sample more in conditions when only the top three ranking options are rewarded (in all conditions but the full condition), compared to when all choices are rewarded depending on the value of the chosen option (in the full condition), leading to more prominent undersampling bias in all conditions compared to the full condition. Participants’ sampling biases seem best explained by whether they feel there is an intrinsic cost / reward value associated with further sampling (i.e., the CS model). There were relatively few consistent differences between the behaviour of the SV and OV versions of either the IO or theoretical models.

This suggests that economic-based tasks cannot (reliably) produce oversampling even when copying the same methods and ideal observer model as used in tasks using pictures to present option values, which do show oversampling (Furl et al., 2019; van de Wouw et al., 2022). We conclude that oversampling in those studies must not arise specifically from any of the methods details we consider here but rather from the content domain of these studies, which used pictures instead of prices (e.g., attractive faces, foods, holiday destinations).

In a surprising finding, we predicted that the methods features we introduced into the “full” conditions in our pilot and Studies 1, 2 and 3 would lead to oversampling bias (as in Furl et al., 2019, van de Wouw, 2022). Yet, instead of observing oversampling bias, these conditions merely reduced the undersampling bias to the point that a higher sample size (Study 2) was needed to determine to what extent a bias exists. We surmise that there is still at least one more factor, not considered in the present study, that is needed to switch behaviour from undersampling to unambiguous oversampling, for the same sequence length (Previous studies showing oversampling also used sequence length 12, as we also predominantly did here). This factor may be the domain: picture based versus numeric / economic. Indeed, as we suggested above, one possibility is that participants may find sampling to be differentially rewarding, depending on the stimulus domain. Another possibility is that sampling rates may depend on the shape of the generating distribution. Previous studies have shown that the shape of the generating distribution can modulate sampling rate, as shown using artificially-manipulated distributions of numerical stimuli (Baumann et al., 2020; Guan & Lee, 2018), and relatively natural distributions from picture-based domains (van de Wouw et al., 2022).

There are some important methodological issues worth mentioning, that should be relevant when designing future studies in this field. The first issue relates to the potential concern that the apparent recalcitrant rigidity of participants’ sampling behavior occurs because some unknown feature of our paradigm prevents measurement of the true effects of sampling. We added Study 3, in part, to assuage this concern by showing successful replication of an effect of sequence length on participant sampling. Nevertheless, it is apparent that participants do not adjust their sampling behaviour with ease. The second issue relates to one of the more obvious differences between paradigms previously showing undersampling (e.g., Costa & Averbeck, 2015) and those showing oversampling (e.g., van de Wouw, 2022). Namely, the former implement their IO models using objective price value and the latter implement their IO models using subjective values obtained in a previous rating phase. In the current study, for the most part, OV and SV versions of ideal observer and theoretical models showed only relatively minor differences in behavioural performance and model fitting. We conclude that this difference cannot account for different sampling biases, and that from a practical standpoint it makes little difference which one uses when modelling. The third issue concerns how participants learn the generating distribution of option values before engaging with the optimal stopping task. Previous research has tried several different approaches to control or identify the generating distribution upon which participants operate in optimal stopping tasks. Baumann et al. (2020), for example, included a learning phase prior to the optimal stopping task to ensure that participants were acquainted with the generating distribution. Like Lee and Courey (2020), they implemented visual presentations of abstract mathematical probability distributions. Participants were asked to draw a histogram on which they received feedback to ensure their understanding of the distribution. According to Goldstein and Rothschild (2014), such a graphical elicitation technique can lead to rather accurate representations of probability distributions in participants. Nevertheless, it is unlikely that people learn beliefs about option probabilities in the real world (e.g., when renting an apartment, or buying a smartphone) by memorising images of statistical distributions. Instead, they are more likely to build up probabilistic beliefs from frequent sequential encounters with other options. The initial ratings phase we used here provides a degree of incidental sequential encounters with option values. Nevertheless, our data here suggests that participants’ sampling behaviour does not depend much on whether there is any pre-exposure to option values within the study or not. It is possible that participants do not use any prior distribution, although the CO heuristic (which assumes no beliefs about the prior generating distribution) did not fit participants’ behaviour as well as a model that did assume such a distribution (i.e., the CS model). A fourth issue concerns how participants learn from repeated engagements with sequences, as studies of the secretary problem (in which participants may not have knowledge of a prior distribution) show participants’ sampling rates can change from sequence to sequence as participants learn (Goldstein et al., 2020). However, we did not find learning effects across sequences here, consistent with previous reports of studies on full-information problems (Lee, 2006).