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Authors
Abalakin, Nikita
Giese, Helge
Wegwarth, Odette

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Nikita Abalakin (nikita.abalakin@charite.de)[1], Helge Giese[1] & Odette Wegwarth[1,2]
[1]Charité - Universitätsmedizin Berlin, Charitépl. 1, 10117 Berlin Germany
[2]Center for Adaptive Rationality, Max-Planck-Institute for Human Development, Berlin Germany

Abstract

Risk communication often relies on descriptive probabilities, yet there is a general preference for experience-based impressions that can be biased by small samples. Interactive simulations can combine both modes, but evidence is mixed and key design features remain confounded. In two online experiments (N = 422; N = 360), we tested how features of simulated experience affect expected-value maximization (EV-Max) in monetary loss gambles. Probabilities were communicated using icon arrays only, and each option involved two independently co-occurring losses. In Experiment 1, the presentation format had only marginal effects, with no advantage for active sampling, whereas sampling without replacement robustly increased EV-Max choices. In Experiment 2, sampling control did not affect EV-Max choices; accumulative displays yielded only marginal EV-Max gains but increased EV-Max preference, confidence, perceived informativeness, and search length. Overall, increased autonomy was largely irrelevant, while reducing sampling noise and using accumulative summaries appear beneficial for risk communication.

Keywords: description-experience gap; description-based learning; experience-based learning; sequential learning; experience simulation.

Introduction

Risk assessment is integral to everyday decision making, and how people perceive probabilities strongly shapes their choices. Effective risk communication is therefore central in domains such as economics, environmental science, and healthcare (Olschewski et al., 2023). People learn about risk either from descriptions (e.g., numerical probabilities in reports; Wulff et al., 2018) or through experience (observing outcomes over time). Experience often feels more concrete and trustworthy and can dominate descriptive formats (Hertwig et al., 2004; Betsch et al., 2015). Yet experiential samples are typically small, which can bias perceived risk and motivate approaches that combine the strengths of both learning models.

Interactive risk simulations have been proposed as such a bridge: they allow sequential sampling that mimics experiential learning while enabling broader coverage and applied relevance (Hogarth & Soyer, 2015). Simulations have been used for investor risks (Kaufmann et al., 2013), diagnostic tests (Armstrong & Spaniol, 2017), and opioid harms and benefits over time (Wegwarth et al., 2021), but effects are mixed (Wegwarth et al., 2021; Lejarraga et al., 2024). A key challenge is that studies vary on multiple dimensions simultaneously (e.g., slideshows vs. sequential sampling, single vs. multiple outcomes, fact boxes vs. other comparators), making it difficult to identify which simulation features are beneficial.

Most work contrasts experience formats with descriptive formats (Wulff et al., 2018) or compares applications across domains (c.f., Popovic et al., 2019) but rarely isolates specific design features of experience-based learning. Another underexamined issue is that of multiple independent outcomes, common in applied contexts (e.g., medical decisions), which limits generalizability from single-outcome tasks. Here, we disentangle key features of experience-based learning and test their effects on risk perception, focusing on adherence to *expected-value maximization (EV-Max).*

Control over sampling

Active exploration can improve learning (Gijsen et al., 2022) and promote EV-consistent choices via enhanced numerical processing (Appelhoff et al., 2022). People also select observations strategically to test hypotheses (Markant & Gureckis, 2014), which may increase engagement (Murayama et al., 2015). However, control can also amplify confirmation bias and selective processing (Jonas et al., 2001; Kaanders et al., 2022), feel burdensome in complex environments (Sullivan-Toole et al., 2017), or reduce engagement when control is perceived as irrelevant (Katz & Assor, 2006). Because passive sequential observation may rely on similar learning mechanisms (Gonzalez & Dutt, 2011), it remains unclear whether autonomy in option selection is essential in experience-based learning.

Generation process

Many active sampling paradigms effectively sample with replacement and may undersample rare events, especially at small sample sizes (Haines et al., 2023). Some applied simulations instead sample without replacement, preserving the intended frequencies while randomizing order (Wegwarth et al., 2021, 2022). Classic experience–description comparisons have confounded learning mode with generation process: experience typically uses with-replacement sampling, whereas descriptive formats resemble "complete distribution" presentations. This leaves open whether performance differences reflect experiential cognition or

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distortions introduced by sampling variability (Hau et al., 2010).

Aggregation of information

In classic sampling tasks, samples disappear and participants rely on memory-based probability representations (Hertwig et al., 2004), which can produce recency effects and apparent underweighting of small probabilities (Hertwig & Erev, 2009; Rakow & Newell, 2010). Accumulative formats (tables/icon arrays that remain visible) should reduce working-memory demands via cognitive offloading (Risko & Gilbert, 2016; Kopsacheilis, 2018) and may stabilize search (Hills & Hertwig, 2010). Yet Hau et al. (2010) found similar performance with and without records, and accumulative summaries can become harder to interpret as magnitudes grow, especially under low numeracy (Peters et al., 2006). Persistent displays may also shift processing toward description-like mechanisms and attenuate sequential-learning advantages (Barron & Erev, 2003), and can reduce later recall (Sparrow et al., 2011). Direct tests in risk communication therefore remain needed.

Present study

In this study, we aimed to test these features of experience-based learning. We conducted two experiments testing different combinations of those features. We excluded explicit numerical information and used only icon arrays as a visual representation of probabilities. To understand how the features affect rational decision making, we measured adherence to the EV-Max strategy. To facilitate broader application, each option in each choice set featured two possible independently co-occurring outcomes.

Experiment 1

In the first experiment, we aimed to test presentation format (static, passive sampling and active sampling) and generation process (with and without replacement) while keeping external factors like sample size and memory effects constant.

A central theoretical question in experience-based learning is whether its commonly observed advantages arise from the informational structure of sequential sampling or from the cognitive processes enabled by active, self-directed exploration (Markant & Gureckis, 2014; Wulff et al., 2018). To test this, we compared active sampling with passive sequential sampling and static presentations of the same probabilistic information. If active control contributes uniquely to EV-Max—via mechanisms such as selective exploration, strategic search, or enhanced metacognitive engagement—then the active condition should yield higher EV-Max choices than the passive-sequential and static formats. We therefore hypothesized that **active sampling will lead to greater EV-Max than passive sequential sampling and static presentation formats (H1)**.

We also compared two sampling generation processes. In the sampling without replacement condition, all participants were presented with the same distributions, but in varying order. In the sampling with replacement condition, each event was drawn from the same distribution as in the condition without replacement, providing each participant with a different final distribution of events, similar to the generation process tested in choice experiments (c.f., Popovic et al., 2019). Although the noise introduced by the sampling generation process is bidirectional, sometimes making EV differences easier and other times harder to detect, the without-replacement generation process communicates the modeled frequencies without distortion, resulting in a more stable internal representation of the distribution, supporting more adherent decision making (Hau et al., 2010). Therefore, we hypothesized that **the generation process without replacement will facilitate the adoption of EV-Max compared to the generation process with replacement (H2)**.

Method

Participants

A power analysis conducted using G*Power 3 software indicated that approximately 390 participants would be required to detect a medium main effect ($f=0.2$) with $\alpha=.05$ and a power of $1-\beta=.95$ (Faul et al., 2007). Participants were recruited via the research platform Prolific. Participants younger than 18 years old were excluded from the study. The participants who participated in a previous experiment with a similar design were also excluded. The final sample comprised 422 participants (51% female).

Procedure

After providing informed consent, participants completed a brief sociodemographic survey. Eligible participants were randomized into one of six experimental conditions (3×2 design: presentation format × generation process), and the order of gamble presentations was algorithmically shuffled by the survey platform. Additionally, gamble option presentation sides (left/right) were counterbalanced.

After randomization, instructions for the assigned condition were displayed, followed by a practice run. The practice run featured a gamble with a dominant option, where the dominant option had a significantly better outcome probability than the other option. After making a choice, participants answered follow-up questions about the practice gamble including the preference and confidence ratings, as well as perceived losses and perceived loss probabilities for each option. The primary task followed immediately after. Upon completing the experiment, participants were debriefed and redirected to Prolific. Participants received a base payment of $4 for their participation, with the opportunity to earn up to an additional $5 based on their performance during the experiment. Depending on the condition, the study took 5 to 84 minutes to complete (*Mdn* = 22 minutes).

Design

This online experiment utilized a 3 (*presentation format*: static vs. passive sampling vs. active sampling) × 2 (*generation process*: sampling with vs. without replacement) between-subjects design. The primary task involved making choices between two monetary gamble *options* (F and J), each with two possible monetary *losses* (bigger and smaller). The losses were independently co-occurring and identical for both options; the only difference was in the probabilities associated with each loss. The *event* is thus defined as one sample, which entailed four possible outcomes: both a bigger and a smaller loss, the occurrence of either a bigger or a smaller loss alone, or no loss at all. The final visual display shows the individual probabilities of big and small losses displayed in the form of icon arrays for each option. The joint probabilities for both losses or no loss had to be inferred by participants themselves. The playing of the gamble, or a final choice, would entail the drawing of the event from these distributions and summation of resulting bigger and smaller losses. The data for the study, pre-registration protocols as well as video demonstration of each condition are available at OSF (https://osf.io/c6qxz/).

The *presentation format* refers to how information was presented to participants. In the static format, participants were shown complete icon arrays, with one icon per array (for bigger and smaller loss) representing a bigger loss (blue icons), smaller loss (yellow icons) and no loss (grey icons). Initially, icons were displayed in an unsorted manner, followed by a sorting animation to make the final appearance of the icon arrays comparable to standard risk communication formats, where icon arrays are typically presented in a sorted manner. In the static condition, we chose to first display unsorted arrays, followed by a sorting animation, to match the final visual state participants would see in the passive and active sampling formats. The static format serves as an alternative to the description format in classical gambling tasks, as participants do not experience the progression of the information distribution. This reflects the core difference between experience-based and description-based formats—whether probabilistic information is presented sequentially event-by-event or as a complete summary. In the passive sampling format, participants observed the progression of sampling events but could not choose from which option it was sampled. Events appeared in the center of the screen, represented by a blue and yellow striped icon for occurrence of both losses, a blue icon for occurrence of only a bigger loss, a yellow icon for occurrence of only smaller loss, and a grey icon for occurrence of no loss. After the short presentation, the icons moved to their designated areas, remaining visible until all events were sampled. The icons were subsequently sorted, as in the static condition. The active sampling format was identical to the passive sampling condition, except participants could choose from which option they would see the events. The sample size was determined by researchers; therefore, when participants reached the event limit for one of the options, they had to sample the remaining events from the other option. This was done in order to ensure clear differences between the two generation processes.

The *generation process* factor introduced two conditions: sampling events with replacement and sampling without replacement, independent of the *presentation format*. In the generation process with replacement, events were sampled from the underlying distribution one at a time, without adjusting the distribution for previously sampled events. Consequently, participants in the with-replacement group received a distribution with sampling noise, which differed for each participant. In contrast, in the without-replacement condition, the underlying distribution was updated after each sample by excluding already shown events. This resulted in the same exact distribution being presented to all participants in the without-replacement group. The search length was fixed by the researchers in both with- and without-replacement conditions and included 10 samples per option, which ensured that the underlying distribution remained unchanged in the generation process without replacement.

Materials

The gamble probabilities were automatically generated to meet specific restrictions (such as different loss probabilities, EVs, joint probabilities for two options), ensuring a variety of strategy combinations (like EV-Max, loss avoidance, joint probability avoidance) that participants could follow for each gamble. Full overview of gambles and the derivation of the superior options for each gamble are available at OSF (https://osf.io/c6qxz/).

We modified the gambles to fit probabilities in units of 10 percent as 10 events were presented per option. We used gambles covering only the loss domain, where the best result would be 0$ (no loss). This was done to enable a more meaningful comparison with fact boxes where probabilities are described only for negative events (e.g., symptoms, side effects) in line with recommendation from the Harding Centre for Risk Literacy. By focusing exclusively on negative outcomes, we created a domain in which heuristics are based on risk minimization.

Measures

If participants selected the option that would theoretically maximize the EV for a given gamble, a score of 1 was recorded for that gamble, otherwise 0 was recorded for the gamble. We used this as our primary outcome variable.

After making a choice, participants answered follow-up questions about the gamble including their preference for their choice and their *confidence in* the choice (on a 0–100 scale). Participants' preference levels for their choice were transformed to negative values if the chosen gamble option was not aligned with the EV-Max option, so that the final value—*preference for EV-Max choice*—for each gamble ranged from -100 (strong preference against the EV-Max choice) to 100 (strong preference for the EV-Max choice). *The preference for EV-Max choice* and *the confidence ratings* were averaged across the 10 gambles for each participant. At the end of the experiment, participants were asked to rate how informative they found their assigned format (on a 0–100 scale)—*the informativeness rating*.

Data analysis

We conducted a logistic mixed-effects regression to examine the effects of *presentation format* (static vs. passive sampling vs. active sampling) and *generation process* (with vs. without replacement) on the likelihood of selecting the EV-Max option, including random intercepts for gamble ID and participant ID in order to test our main hypotheses.

Additionally, we implemented a 3 (*presentation format*: static, passive sampling vs. active sampling) × 2 (*generation process*: with vs. without replacement) between-subjects ANOVA to examine the effects of display variants on participants' preference for EV-Max, participants' confidence and how informative they found the formats to test the hypotheses for the secondary outcomes.

Results

Participants differed marginally in their choices in accordance with EV-Max by *presentation format*. Passive sampling participants were marginally more likely to select the EV-Max option than participants in the static condition, OR = 1.23, SE =0.11, p =.056, *95% CI* [1.00, 1.53], with no significant difference from the active sampling, OR = 1.18, SE =0.11, p =.16, *95% CI* [0.95, 1.47]. Participants in the static and active sampling conditions were comparably likely to select the option with higher EV, OR = 1.04, SE =0.09, p =.89, *95% CI* [0.84, 1.29]. **Thus, our first hypothesis was not supported (H1).**

In line with our expectations, participants in the generation process without replacement condition made more choices aligned with the EV-Max strategy compared to those in the generation process with replacement condition, OR = 1.27, SE =0.059, p =.001, *95% CI* [1.10, 1.47]. **This confirms our second hypothesis (H2).**

Secondary outcomes

The EV-Max preference differed by presentation format, $F(2, 416)$ =3.32, p = .037, η_p^2 = .016. Pairwise comparisons revealed a marginal significant difference between passive and static formats, $t(416)$ =2.38, p =.053, d =.282, with participants in the passive group showing higher EV-Max preference. No other significant comparisons between presentation formats were revealed, all $t(416) \leq$-2.05, $p \geq$.117, $d \leq$-.247. Participants had a higher preference for EV-Max choices when the generation process was applied without replacement compared to when it was applied with replacement, $F(1, 416)$ =10.78, p =.001, η_p^2 =.025.

The presentation format did not influence participants' confidence in their choices, $F(2, 419)$ =0.46, p =.63, η^2 =.002.

Overall, presentation formats differed in their perceived informativeness, $F(2, 419)$=5.44, p=.005, η^2=.025. Participants found the static format to be more informative than the active sampling format, $t(416)$ =-3.25, p =.004, d =-.387, with all other comparisons being non-significant, all $t(416) \leq$2.06, $p \geq$.116, $d \leq$-.244.

There were no interaction effects between presentation format and generation process in any of the analyses.

Discussion

The presentation format had only a limited effect. Contrary to our expectations and to previous research (Wulff et al., 2018), active sampling—where participants experienced sequential learning and actively chose the order of options—did not lead to greater implementation of the EV-Max strategy compared to other formats. Passive sampling, on the other hand, was marginally better than the other formats. Although this marginal effect may not be sufficient to declare passive sampling the better format, the absence of superiority for active sampling leads us to reject the hypothesis that control over exploration plays a significant role in EV-Max adherence. Therefore, one might argue that sequential learning alone appears to offer the greatest advantages in risk communication. This interpretation is also consistent with reported similarities in the core cognitive mechanisms underlying learning from experience in both active and passive exploration (Gonzalez & Dutt, 2011). In contrast, in the active sampling condition, observations might carry more subjective weight precisely because they result from autonomous choices, which can influence attention and promote confirmation bias (Kaanders et al., 2022).

In the with-replacement condition, each outcome was extracted independently, introducing sampling variability that resulted in participant-specific noise in the observed outcome distributions—particularly for rare events, sometimes missed entirely. This sampling error can distort internal representations of probabilities, rendering even distinctly defined EV differences more challenging to discern. In contrast, the without-replacement condition ensured that all participants encountered a stable and precise frequency representation of the underlying probabilities. This more structured presentation mitigates biases such as the underweighting of rare events (Hertwig et al., 2004) and memory-based noise in probability estimation (Wulff et al., 2018), providing a clear advantage for risk communication contexts where accurate comprehension of probability distributions is critical. Therefore, for transparent risk communication purposes as opposed to experimental research, the generation process without replacement should be applied similarly to the approach used in Wegwarth and colleagues' (2021) studies.

Experiment 2

In the second experiment, we aimed to test control over sampling (full and partial) and display duration (transient and accumulative).

To examine whether having full control over the experience enhances EV-Max, we compared the sampling format with full control over the sampling size and from which option to sample with partial control where the sampling is implemented passively, meaning participants can only control the sample size but not from which option the event is sampled. Based on the result of the study conducted by Appelhoff and colleagues (2022) and reported advantages of selective, self-directed learning (Markant & Gureckis, 2014), our hypothesis was that **the sampling format with**

full control will yield greater use of the EV-Max strategy compared to the sampling format with partial control (H3).

We also compared two display durations. The transient display duration implemented the classical sampling paradigm, where the event disappears after each sample, forcing participants to rely on their memory and inner probabilities representations. In the accumulative condition, the events stayed on the screen and were summarized in an icon array until the final decision was made. Since summarized icon arrays should lead to fewer sampling errors (Risko & Gilbert, 2016; Kopsacheilis, 2018), we hypothesized that **the accumulative display of information will yield greater use of the EV-Max strategy compared to the transient formats (H4)**.

Participants

A power analysis performed with G*Power 3 indicated that around 327 participants would be needed for the study in order to produce a medium main effect (f = 0.2) with $\alpha = .05$ and a power of $(1 - \beta) = .95$ (Faul et al., 2007). Participants were recruited via the research platform Prolific. Participants younger than 18 years old as well as those who participated in experiment 1 were excluded. The final sample comprised 360 participants (52% female).

Design

This experiment utilized a 2 (*sampling format*: full control vs. partial control) × 2 (*display duration*: transient vs. accumulative) between-subjects design. The primary task was identical to that of Experiment 1.

The *sampling format* refers to how much control over sampling participants had. In the full control sampling, participants had complete control over the sampling procedure: search length and from which option they want to see an event. The participants had to press the corresponding key to select the option F or J, hence the labels. In the partial control sampling, participants only had control over the search length, but not from which option they would see an event. For each sample they had to press the key "h" to continue sampling. In both conditions participants could stop sampling any time after seeing at least one event from each option by clicking "stop sampling" at the bottom of the screen. The upper limit of sampling was set to 36 events per option.

The *display duration* describes how long events stayed on the screen after they had been sampled. The transient display format corresponds to a classical sampling paradigm where the event disappears after each sample. In this study, the events still move to the designated area of the specific loss, and disappear after the participant decides to sample the next event or is ready to make the final decision. In the accumulative display, the progression is the same as the transient one, but after the events move to their position on the screen, they stay there until the participant is ready to make the decision, building icon arrays for each option and each loss.

Procedure

The procedure was identical to Experiment 1.

Materials

We used the same set of gamble probabilities as in Experiment 1.

Measures

The measurements were identical to those of Experiment 1. Additionally, we recorded the search length, the number of samples participants drew.

Data analysis

Similar to Experiment 1, we conducted a logistic mixed-effects regression to examine the effects of *sampling format* (full vs. partial control) and *display duration* (transient vs. accumulative) on the likelihood of selecting the EV-Max option, including random intercepts for gamble ID and participant ID in order to test our main hypotheses.

Additionally, we implemented a 2 (*sampling format*: full control vs. partial control) × 2 (*display duration*: transient vs. accumulative) between-subjects ANOVA to examine the effects of display variants on participants' preference for EV-Max, participants' confidence and informativeness levels to test the hypotheses for the secondary outcomes.

As an exploratory analysis, we analyzed search length as an outcome, testing the effects of the two main predictors applying mixed linear regression with random intercepts for gamble ID and participant ID. We log-transformed the search length in the analysis to better fit assumptions of the model. We then included search length as a predictor in the primary mixed-effects logistic regression to examine its effect on the probability of selecting the EV-Max option.

Results

Contrary to our expectations, control over sampling did not affect adherence to the EV-Max strategy. Participants with full and partial sampling controls were comparably likely to select the EV-Max option, $OR = 0.92$, $SE = 0.07$, $p = .25$, *95% CI* [0.8, 1.06]. Thus, **we did not find support for our first hypothesis (H3)**.

People who observed information in the accumulative format were marginally more likely to select EV-Max options in comparison with participants whose information displays were transient, $OR = 1.13$, $SE = 0.08$, $p = .09$, *95% CI* [0.98, 1.3], providing **only limited support for our second hypothesis (H4)**.

Secondary Outcomes

Participants with full and partial sampling control had similar preferences for the EV-Max option, $F(1, 356) = 0.535$, $p = .46$, $\eta_p^2 = .002$. Mirroring choice effects, participants with accumulative display duration expressed higher preference for the EV-Max option compared to ones with transient display, $F(1, 356) = 6.88$, $p = .009$, $\eta_p^2 = .019$.

Control over sampling did not influence participants' confidence in their choice, $F(1, 356) = 0.06$, $p = .8$, $\eta_p^2 = .000$. Participants who observed accumulative displays were more confident than participants with transient displays, $F(1, 356) = 7.67$, $p = .006$, $\eta_p^2 = .021$.

Participants with the full control over sampling found it to be more informative than participants with partial control, $F(1, 356) = 4.38$, $p = .04$, $\eta_p^2 = .012$. Participants also rated the accumulative display duration as more informative than the transient one, $F(1, 356) = 13.37$, $p < .001$, $\eta_p^2 = .036$.

There were no interaction effects between the two predictors in any of the analyses.

Search length

Participants with partial sampling control sampled more events than those with full control, $b = -0.1$, $SE = 0.038$, $p = .011$, *95% CI* [-0.17, -0.02]. The same effect was observed in the accumulative display duration, where participants sampled more events on average than in transient display duration, $b = 0.18$, $SE = 0.038$, $p < .001$, *95% CI* [0.1, 0.25].

When search length was used as a covariate in the main hypotheses model, the effects of the two main predictors were similar to the main analyses. Participants who sampled more events were also more likely to choose the EV-Max option, $OR = 1.2$, $SE = 0.054$, $p < .001$, *95% CI* [1.1, 1.31]. When controlling for the differing sample sizes, partial control over sampling was associated with slightly higher odds of EV selection, $OR = 1.03$, *95% CI* [1.01, 1.07]. Similarly, an accumulative display was associated with slightly higher odds of EV-Max selection compared to transient display duration, $OR = 1.06$, *95% CI* [1.03, 1.12].

Discussion

Our results indicate that granting full control over both which options to probe and how long to sample did not yield more optimal EV-Max choices than partial control limited to sample size. One possible reason is that having full control can invite smaller sample sizes and recency-weighted updating, which distort subjective probabilities (Hertwig & Erev, 2009; Wulff et al., 2018), and can also trigger confirmation-biased information selection (Kaanders et al., 2022), offsetting any gains from autonomy (Gijsen et al., 2022). These results challenge the idea that having autonomy over sampling leads to more effective learning (Markant & Gureckis, 2014) and boosts numerical processing (Appelhoff et al., 2022).

The accumulative display of probabilistic information did not significantly increase EV-Max choices. This finding is similar to results reported by Hau and colleagues (2010), who found that the transient format produced EV-Max comparable to the records condition, where events were accumulated. The argument can be made that, independent of summarization, people acquire gist knowledge about probabilities from the sequential presentation of information, which in turn contributes to more optimal decision making (Reyna et al., 2016). The accumulative display did have clear advantages for proximal judgments: participants reported a higher EV-Max preference, greater confidence, and higher perceived informativeness. Accumulating information may have supported participants' verbatim knowledge, which in turn could have promoted a slightly higher degree of EV-Max choices. It also prompted participants to sample more events. These benefits are consistent with cognitive offloading accounts: persistent displays lower working-memory demands and stabilize integration, thereby reducing recency-driven distortions (Risko & Gilbert, 2016; Wulff et al., 2018).

General discussion

In this study, we attempted to disentangle several features that contribute to the effects of experience-based learning and to understand how these features influence cognitive risk perception, as well as how they could be implemented in risk communication tools such as interactive risk simulations, which are gaining more widespread adoption across various fields (Hogarth & Soyer, 2015; Kaufmann et al., 2013; Wegwarth et al., 2021).

Taking results together, it suggests that the amount of control appears largely irrelevant to achieving EV-Max choices. Moreover, passive sequential observation was marginally better for EV-Max adherence in both studies. It seems that the sequential presentation of events might be enough to elicit the reported effects of experience-based learning (Wulff et al., 2018). However, these advantages of passive sampling were statistically significant only when compared with static presentation in Experiment 1 and emerged only as an indirect effect via increased search length in Experiment 2.

Interestingly, static presentation format and sampling with full control were judged to be more informative, yet these advantages do not seem to translate into better decision making. This absence of improved decision making might be attributed to the lack of motivation in the study: the monetary incentives might have been insufficient to engage participants and raise their motivation to fully explore the options.

The accumulative display duration was only marginally better in guiding participants toward EV responses. This was surprising, given that across all secondary outcomes the accumulative display duration had a clear advantage over the transient display duration. These results point to the beneficial use of accumulative display in the risk communication domain.

The generation process without replacement also proved effective in guiding participants toward EV responses and outperformed with-replacement sampling across secondary outcomes.

Together, these findings point to the advantages of simpler, more passive sampling formats over formats with active option exploration when the goal is to elicit more optimal decision making and foster better risk perception. They also provide a clear implication for future design of interactive simulation programs in risk communication, promoting use of the generation process without replacement and accumulative display duration.

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References

Appelhoff, S., Hertwig, R., & Spitzer, B. (2022). Control over sampling boosts numerical evidence processing in human decisions from experience. *Cerebral Cortex*, *33*(1), 207–221. https://doi.org/10.1093/cercor/bhac062

Armstrong, B., & Spaniol, J. (2017). Experienced Probabilities Increase Understanding of Diagnostic Test Results in Younger and Older Adults. *Medical Decision Making,* *37*(6), 670–679. https://doi.org/10.1177/0272989X17691954

Barron, G., & Erev, I. (2003). Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making*, *16*(3), 215–233. https://doi.org/10.1002/bdm.443

Betsch, C., Haase, N., Renkewitz, F., & Schmid, P. (2015). The narrative bias revisited: What drives the biasing influence of narrative information on risk perceptions? *Judgment and Decision Making*, *10*(3), 241–264. doi:10.1017/S1930297500004654

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Gijsen, S., Grundei, M., & Blankenburg, F. (2022). Active inference and the two-step task. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-21766-4

Gonzalez, C., & Dutt, V. (2011). Instance-based learning: Integrating sampling and repeated decisions from experience. *Psychological Review, 118*(4), 523–551. https://doi.org/10.1037/a0024558

Haines, N., Kvam, P. D., & Turner, B. M. (2023). Explaining the description-experience gap in risky decision-making: learning and memory retention during experience as causal mechanisms. *Cognitive Affective & Behavioral Neuroscience*, *23*(3), 557–577. https://doi.org/10.3758/s13415-023-01099-z

Hau, R., Pleskac, T. J., & Hertwig, R. (2010). Decisions from experience and *statistical probabilities*: Why they trigger different choices than a priori probabilities. *Journal of Behavioral Decision Making,* *23*(1), 48–68. https://doi.org/10.1002/bdm.665

Hills, T. T., & Hertwig, R. (2010). Information search in decision from experience. *Psychological Science*, *21*(12), 1787–1792. https://doi.org/10.1177/0956797610387443

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from Experience and the Effect of Rare Events in Risky Choice. *Psychological Science*, *15*(8), 534–539. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. https://doi.org/10.1016/j.tics.2009.09.004

Hogarth, R. M., & Soyer, E. (2015). Providing information for decision making: Contrasting description and simulation. *Journal of Applied Research in Memory and Cognition,* *4*(3), 221–228. https://doi.org/10.1016/j.jarmac.2014.01.005

Jonas, E., Schulz-Hardt, S., Frey, D., & Thelen, N. (2001). Confirmation bias in sequential information search after preliminary decisions: An expansion of dissonance theoretical research on selective exposure to information. *Journal of Personality and Social Psychology*, *80*(4), 557–571. https://doi.org/10.1037//0022-3514.80.4.557

Kaanders, P., Sepulveda, P., Folke, T., Ortoleva, P., & De Martino, B. (2022). Humans actively sample evidence to support prior beliefs. eLife, 11. https://doi.org/10.7554/elife.71768

Katz, I., & Assor, A. (2006). When choice motivates and when it does not. *Educational Psychology Review*, *19*(4), 429–442. https://doi.org/10.1007/s10648-006-9027-y

Kaufmann, C., Weber, M., & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science*, *59*(2), 323–340. https://doi.org/10.1287/mnsc.1120.1607

Kopsacheilis, O. (2018). The role of information search and its influence on risk preferences. *Theory Decis 84,* 311–339. https://doi.org/10.1007/s11238-017-9623-y

Lejarraga, T., Pachur, T., Frey, R., & Hertwig, R. (2016). Decisions from Experience: From Monetary to Medical Gambles. *Journal of Behavioral Decision Making*, *29*(1), 67–77. https://doi.org/10.1002/bdm.1877

Lejarraga, T., Ranganathan, K., & Wulff, D. U. (2024). Can simulated experience be harnessed to help people make investment decisions? *Judgment and Decision Making*, *19*. https://doi.org/10.1017/jdm.2024.17

Markant, D. B., & Gureckis, T. M. (2014). Is it better to select or to receive? Learning via active and passive hypothesis testing. *Journal of Experimental Psychology: General, 143*(1), 94–122. https://doi.org/10.1037/a0032108

Murayama, K., Matsumoto, M., Izuma, K., Sugiura, A., Ryan, R. M., Deci, E. L., & Matsumoto, K. (2015). How self-determined choice facilitates performance: A key role of the ventromedial prefrontal cortex. *Cerebral Cortex*, *25*(5), 1241–1251. https://doi.org/10.1093/cercor/bht317

Olschewski, S., Luckman, A., Mason, A., Ludvig, E. A., & Konstantinidis, E. (2023). The Future of Decisions From Experience: Connecting Real-World decision problems to cognitive processes. *Perspectives on Psychological Science*, *19*(1), 82–102. https://doi.org/10.1177/17456916231179138

Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences*, *20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological science*, *17*(5), 407–413. https://doi.org/10.1111/j.1467-9280.2006.01720.x

Popovic, N. F., Pachur, T., & Gaissmaier, W. (2019). The gap between medical and monetary choices under risk persists in decisions for others. *Journal of Behavioral Decision Making*, *32*(4), 388–402. https://doi.org/10.1002/bdm.2121

Rakow, T. and Newell, B.R. (2010). Degrees of uncertainty: An overview and framework for future research on experience-based choice. *J. Behav. Decis. Making, 23*: 1-14. https://doi.org/10.1002/bdm.681

Reyna, V. F., Corbin, J. C., Weldon, R. B., & Brainerd, C. J. (2016). How fuzzy-trace theory predicts true and false memories for words, sentences, and narratives. *Journal of Applied Research in Memory and Cognition*, *5*(1), 1–9. https://doi.org/10.1016/j.jarmac.2015.12.003

Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, *333*(6043), 776–778. https://doi.org/10.1126/science.1207745

Sullivan-Toole, H., Richey, J. A., & Tricomi, E. (2017). Control and effort costs influence the motivational consequences of choice. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00675

Wegwarth, O., Wind, S., Goebel, E., Spies, C., Meerpohl, J. J., Schmucker, C., Schulte, E., Neugebauer, E., & Hertwig, R. (2021). Educating pharmacists on the risks of strong opioids with descriptive and simulated experience risk formats: a randomized controlled trial. *MDM Policy & Practice*, *6*(2). https://doi.org/10.1177/23814683211042832

Wegwarth, O., Spies, C., Ludwig, W., Donner-Banzhoff, N., Jonitz, G., & Hertwig, R. (2022). Educating physicians on strong opioids by descriptive versus simulated-experience formats: a randomized controlled trial. BMC Medical Education, 22(1). https://doi.org/10.1186/s12909-022-03797-7

Wulff, D. U., Mergenthaler-Canseco, M., & Hertwig, R. (2018). A meta-analytic review of two modes of learning and the description-experience gap. *Psychological Bulletin*, *144*(2), 140–176. https://doi.org/10.1037/bul0000115