AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Experimental Psychology: General

ISSN: 0096-3445

2024, Vol. 153, No. 6, 1628–1643
https://doi.org/10.1037/xge0001586

Uncertainty-Modulated Attentional Capture: Outcome Variance Increases Attentional Priority

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Our prior experiences shape the way that we prioritize information from the environment for further processing, analysis, and action. We show in three experiments that this process of attentional prioritization is critically modulated by the degree of uncertainty in these previous experiences. Participants completed a visual search task in which they made a saccade to a target to earn a monetary reward. The color of a color-singleton distractor in the search array signaled the reward outcome(s) that were available, with different degrees of variance (uncertainty). Participants were never required to look at the colored distractor, and doing so would slow their response to the target. Nevertheless, across all experiments, participants were more likely to look at distractors associated with high outcome variance versus low outcome variance. This pattern was observed when all distractors had equal expected value (Experiment 1), when the difference in variance was opposed by a difference in expected value (i.e., the high-variance distractor had a low expected value, and vice versa: Experiment 2), and when high- and low-variance distractors were paired with the maximum-value outcome on an equal proportion of trials (Experiment 3). Our findings demonstrate that experience of prediction error plays a fundamental role in guiding "attentional exploration," wherein priority is driven by the potential for a stimulus to reduce future uncertainty through a process of learning, as opposed to maximizing current information gain.

Public Significance Statement

Uncertainty is a ubiquitous feature of our experience of the world and may represent a common currency in neural processing. This study demonstrates that our attention is involuntarily drawn to unreliable sources of information even when more reliable or rewarding options are available, highlighting the role of uncertainty as a fundamental motivating force in attentional control. This drive to explore the unknown has broad implications for the way that we gather information from the environment. For instance, prioritizing stimuli whose consequences are currently unknown may be a central way that our attention system facilitates learning: by focusing on uncertain stimuli now, we can learn more about them, reducing our uncertainty when we encounter them again in the future. These findings could also shed light on attentional processes linked to anxiety and gambling, where individual differences in responses to uncertainty may play a central role.

Keywords: attention, information seeking, reward, uncertainty

Supplemental materials: https://doi.org/10.1037/xge0001586.supp

This article was published Online First May 2, 2024.

Rachel Wu served as action editor.

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This work was supported by an Australian Research Council Grant DP200101314. The raw data, experimental scripts, and analysis scripts are available at: https://osf.io/hra94/. Some of the data and ideas in this article were presented at the 2023 Annual Meeting of the Vision Sciences Society. A preprint of this article was made available on PsyArXiv (https://psyarxiv.com/aenu7/).

Daniel Pearson served as lead for data curation, formal analysis, visualization, and writing–original draft and served in a supporting role for supervision. Amy Chong served in a supporting role for formal analysis. Julie Y. L. Chow contributed equally to formal analysis. Jan Theeuwes contributed equally to funding acquisition. Mike E. Le Pelley served as lead for funding acquisition and supervision. Daniel Pearson, Julie Y. L. Chow, Kelly G. Garner, Jan Theeuwes, and Mike E. Le Pelley contributed equally to conceptualization. Daniel Pearson, Amy Chong, and Mike E. Le Pelley contributed equally to methodology. Daniel Pearson and Mike E. Le Pelley contributed equally to software. Daniel Pearson, Amy Chong, and Julie Y. L. Chow contributed equally to investigation. Amy Chong, Julie Y. L. Chow, Kelly G. Garner, Jan Theeuwes, and Mike E. Le Pelley contributed equally to writing–review and editing.

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The complex and stochastic nature of our environment means that every sensation we perceive, prediction we make, and action we take has a degree of associated uncertainty (Bach & Dolan, 2012). Consistent with its ubiquity in our environment, the drive to reduce uncertainty has been implicated in a wide range of fundamental psychological processes, including learning (e.g., Mackintosh, 1975; Pearce & Hall, 1980; Rescorla & Wagner, 1972), memory (e.g., Gruber & Ranganath, 2019), decision-making (Goh et al., 2021; Sharot & Sunstein, 2020), sensorimotor control (e.g., Körding & Wolpert, 2006), and higher order behaviors like social interaction (e.g., FeldmanHall & Shenhav, 2019). Indeed, it has been argued that uncertainty reduction may represent a central unifying principle in brain functioning (e.g., Friston, 2010). This raises the question of how we gather information about uncertainty in the first instance: that is, how encoding is shaped by uncertainty, so that uncertainty-related stimuli are appropriately prioritized (or deprioritized) for further processing. This process of prioritization is implemented and regulated by a set of cognitive mechanisms that are collectively referred to as attention. So to fully understand human behavior in our inherently uncertain environment, it is crucial to understand the factors that influence attentional selection and, thereby, the way that we gather information to minimize uncertainty (Gottlieb, 2023; Gottlieb et al., 2020; Pearson et al., 2022).

Influences on Attentional Selection

Prior research has identified three categories of influences on attentional selection. Goal-directed control describes the process by which attention can be strategically directed based on the observer's goals (Posner, 1980; Yantis & Jonides, 1990). Meanwhile, physically salient stimuli—that is, stimuli that are distinctive based on their physical features (color, size, onset, etc.)—can automatically capture attention even when they are task-irrelevant, viastimulus-driven control (Theeuwes, 1992, 1994; Yantis & Jonides, 1984). More recent research points to a third category of influences—labeled selection history—which refers to instances in which attentional control is influenced by prior experience with stimuli, independently of their physical features and the observer's goals (see Anderson et al., 2021; Theeuwes, 2019).

One component of selection history relates to a stimulus's learned value. Studies of value-modulated attentional capture show that previous experience of the relationship between a stimulus and reward automatically increases the attentional priority of that stimulus (for a recent review, see: Pearson et al., 2022). In one such study, Le Pelley et al. (2019) had participants complete a visual search task in which they had to make a rapid eye movement (saccade) to a shape target (a diamond among circles) to earn rewards. One of the nontarget circles in each search display (termed the distractor) was colored; other shapes were gray. The color of the distractor signaled whether a high or low reward was available on that trial. Importantly, looking at the distractor was counter to the participant's goals, as it would slow their response to the target, making it less likely that they would earn a reward. Nevertheless, participants occasionally looked at the distractor, as would be expected given that the distractor is a color singleton and so captures attention on the basis of its physical salience (Theeuwes et al., 2003). Critically, however, participants were more likely to look at the distractor when it signaled the availability of high reward versus low reward. This suggests that the attentional priority of a physically salient stimulus is further increased as a result of learning about the value of the reward that it signals, such that reward-related stimuli automatically capture attention over stimuli of equivalent salience, even when contrary to task requirements (see also Le Pelley et al., 2015; Pearson et al., 2015).

Attentional Priority, Uncertainty, and Information Gain

Studies investigating how reward shapes attention have typically considered stimuli associated with different levels of expected value: signals of higher (average) value are prioritized for selection over signals of lower value. However, reward-related stimuli can also vary in the certainty with which they signal a reward outcome. Consider a task in which one of two cues appears on each trial: Cue A guarantees a \$5 reward, whereas Cue B signals a coin-flip chance at \$10 or nothing. Both cues signal an equal expected value of \$5, but they differ in the certainty with which they predict the specific outcome that you will receive. Cue A is perfectly predictive of the outcome, resolving all uncertainty about the reward that you will receive (\$5). However, Cue B leaves a degree of uncertainty about which of the two potential outcomes (\$0 or \$10) will occur.

The information provided by a cue regarding subsequent events can be understood via the concept of entropy. Entropy represents the amount of choice available in the selection of outcome events, which influences how surprising each observed outcome is (Shannon, 1948). Other things being equal, entropy increases as a function of the number of distinct event outcomes. For example, rolling a die has greater entropy (2.58 bits) than flipping a coin (1 bit). The information gain provided by a cue can then be quantified in terms of the reduction in entropy that observation of the cue affords: an informative cue takes an observer from a state of high uncertainty (high entropy) to low uncertainty (low entropy). For example, observing Cue A takes us from high entropy (before the trial begins, we do not know if we will receive \$0, \$5, or \$10) to a state of zero entropy (when we see Cue A, we know we will receive \$5). By contrast, observing Cue B does not reduce entropy as far (the outcome may be \$0 or \$10). Cue A therefore provides a greater information gain than Cue B.

Recently, it has been suggested that the attentional priority of a stimulus may increase as a function of information gain (Gottlieb, 2023; Gottlieb & Oudeyer, 2018; Gottlieb et al., 2020). Supporting evidence comes from the neurophysiological literature (e.g., Blanchard et al., 2015; Bromberg-Martin & Hikosaka, 2009; Daddaoua et al., 2016; Foley et al., 2017; Horan et al., 2019; White et al., 2019). For instance, neurons in the monkey parietal cortex increase their firing rate for cues that signal where a target will subsequently appear when that cue carries greater certainty (Foley et al., 2017). Similarly, monkeys preferentially saccade to cues that accurately predict the identity of a future reward over noninformative cues, even when the information provided by these cues cannot be used to influence the outcome that is delivered (e.g., Blanchard et al., 2015; Bromberg-Martin & Hikosaka, 2009). These findings have been taken to suggest that a primary drive of the attention system is to gather information from cues that provide greater information gain to minimize our current uncertainty (Gottlieb, 2023; Gottlieb et al., 2020).

Uncertainty-Modulated Attentional Capture (UMAC)

Recent findings challenge the idea that attentional priority is always increased for cues that provide greater information gain

(Cho & Cho, 2021; Ju & Cho, 2023; Koenig et al., 2017; Le Pelley et al., 2019). For instance, in a follow-up to the value-modulated attentional capture experiment described above, Le Pelley et al. (2019) had participants complete a search task in which a "certain" distractor signaled a 50-point reward with 100% certainty, whereas an "uncertain" distractor signaled 0 points on 50% of trials and 100 points on the other 50% of trials. Consequently, these distractors had equal expected values (50 points) but differed in information gain. If attention acts to prioritize stimuli providing greater information gain, we would expect greater capture by the certain distractor than the uncertain distractor. However, Le Pelley et al. observed the opposite: participants were more likely to have their gaze captured by the uncertain distractor than the certain distractor (see also Cho & Cho, 2021; Ju & Cho, 2023). That is, participants rapidly and selectively prioritized the distractor that provided less information and left unresolved uncertainty about the outcome that would occur, over a distractor that provided full, diagnostic information: an influence of selection history on prioritization that we term UMAC.

Current Versus Future Uncertainty

The UMAC finding is difficult to reconcile with the idea that attentional priority is driven by the extent to which a stimulus resolves current uncertainty. An alternative possibility is that prioritization is based on a stimulus's potential to reduce future uncertainty through a process of learning. If our goal is to understand the relationships between stimuli and outcomes, it is inefficient to focus resources on stimuli whose consequences are already known with certainty. Instead, we should devote resources to the attentional exploration of stimuli whose consequences are currently uncertain, in an attempt to gain a more complete understanding of their predictive status (Beesley et al., 2015; Dickinson, 1980; Le Pelley et al., 2016). By this account, once it is established that the "certain" distractor consistently signals 50 points, there is no potential to reduce uncertainty further by learning more about this stimulus, and so there is no additional benefit to be gained from prioritizing it. By contrast, participants cannot reliably predict the outcome on trials featuring the "uncertain" distractor, so there is a potential benefit to prioritizing it: exploring the features of the "uncertain" distractor might help to discern its "true" predictive status[1] and hence reduce uncertainty when it is encountered in the future.

Prediction Error and Outcome Variance

The idea that attention should be allocated to stimuli whose consequences are uncertain to facilitate learning has been formalized in theories of animal conditioning (e.g., Dayan et al., 2000; Esber & Haselgrove, 2011; Le Pelley, 2004; Pearce & Hall, 1980). A central tenet of these theories is that attentional prioritization of a cue is a function of its associated prediction error: the discrepancy between the outcome it predicts, and the outcome that occurs. For example, expecting to receive $10 and receiving $100 results in a larger prediction error than expecting $10 and receiving $20.

Earlier we introduced entropy as a parameter of uncertainty reflecting the number of distinct ways that an outcome can manifest. Prediction error is also influenced by the amount of discrepancy between the predicted and actual outcome, which relates to the concept of outcome variance[2] as another property of uncertainty: the degree to which outcomes are larger or smaller than the expected (mean) value. Consequently, learning-based theories that conceptualize UMAC as representing attentional exploration (to reduce future uncertainty) anticipate that the effect will be a product not only of the occurrence of distinct outcomes (relating to entropy) but will also be modulated by the degree of the expectancy-violation created by the observed outcomes—which relates to outcome variance.

The current study investigated this possibility. Experiment 1 compared capture by distractors that differed in their associated outcome variance but had equal entropy and expected value. Experiment 2 put the effects of uncertainty in opposition to the effects of expected value, comparing capture by a distractor with high outcome variance and low expected value to a distractor with low outcome variance but high expected value. Experiment 3 provided a stronger test of the influence of uncertainty on attentional priority, by pairing both the high and low uncertainty distractors with the best (i.e., maximum value) outcome available in the experiment on an equal proportion of trials.

Experiment 1

Experiment 1 used a variation on the search task used by Le Pelley et al. (2019), where participants had to make an eye movement to a diamond-shaped target among circles to earn reward, and the color of a distractor signaled the reward outcome(s) that were available. There were three different colors of distractor, each signaling a different pattern of reward outcomes. One of the distractors—the high-variance (HV) distractor—signaled that either 0 or 100 points were available, with equal probability. By contrast, the low-variance (LV) distractor signaled that either 40 or 60 points were available. Consequently, these distractors were associated with equal expected value (50 points) and entropy (both were paired with two distinct outcomes), but differed in variance; see Table 1. The critical question was whether participants would be more likely to have their gaze captured by the HV distractor than the LV distractor, which would provide evidence for a (specific) influence of variance on attentional priority. The third distractor—the no-variance (NV) distractor—consistently signaled that 50 points were available, and so was lower in both entropy and variance than the others; data from this distractor allowed us to verify the general influence of uncertainty on attention demonstrated in prior research (Cho & Cho, 2021; Le Pelley et al., 2019).

Method

Participants and Apparatus

Research reported here was approved by the UNSW Sydney Human Research Ethics Advisory Panel (Psychology). Previous

[1] In the experiment by Le Pelley et al. (2019), there was in fact no further information to be gained about the relationship between the "uncertain" distractor and the reward delivered on each trial, as outcomes were determined probabilistically. Nevertheless, this does not rule out the possibility that prioritization of the uncertain distractor is driven by the potential to reduce future uncertainty through learning, even if in reality (and unknown to participants) this is impossible.

[2] In the current study, prediction error was operationalized in terms of outcome variance. However, other measures of the spread of outcomes around the mean could also be used to characterize prediction error. We return to this idea in the General Discussion.

Table 1
Outcome Parameters for Single-Distractor Trials in Experiment 1

Distractor type	Available reward	Reward probability	Expected value	Entropy (bits)	Variance
HV	0/100	.5/.5	50	1	2,500
LV	40/60	.5/.5	50	1	100
NV	50	1	50	0	0

Note. HV = high variance; LV = low variance; NV = no variance.

studies of UMAC have demonstrated small to medium effect sizes ($d_z = 0.36–0.58$; Cho & Cho, 2021; Le Pelley et al., 2019). Based on an anticipated effect size of $d_z = 0.5$, power analysis using G*Power (Faul et al., 2007) indicated a sample size of 26 participants would provide power of 0.80 in a within-subjects t test. Therefore, we collected data for as many days as required to achieve a sample size of 30 participants. In total, 31 UNSW students participated for course credit. Participants also received a monetary bonus dependent on the number of points that they earned during the task (M = AU$11.10, SD = AU$1.02). At the start of the experiment, participants were asked to select a term to describe their gender from a list of five options: "Man/male," "Woman/female," "Nonbinary," "I use a different term," or "I prefer not to answer." If the participant chose "I use a different term" they were able to enter their preferred term using a free response box. Of the 31 participants, 17 selected man/male and 14 selected woman/female. Participants also reported their age (M = 19.03 years, SD = 1.61 years). Due to a technical failure, two participants did not complete the choice task that followed the search task (see Stimuli and Design), and these two participants plus one extra also did not complete the estimation task and variance awareness test.

Participants were tested using a Tobii Pro Spectrum eye-tracker (600 Hz sample rate) mounted on a 23-in. monitor with 1,920 × 1,080 resolution. Gaze data were down-sampled to 100 Hz for gaze-contingent calculations. Head positioned was stabilized with a chin rest 60 cm from the monitor. Stimulus presentation was controlled by MATLAB using Psychophysics Toolbox extensions (Kleiner et al., 2007).

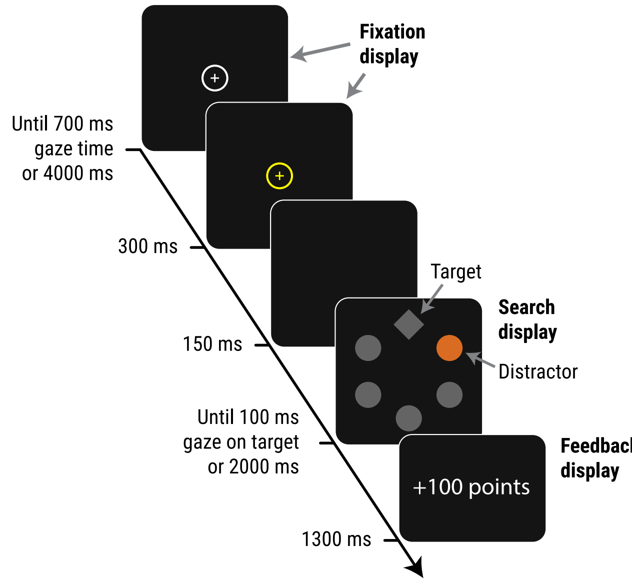
Stimuli and Design

Search Task. The search task was based on Le Pelley et al. (2019). Each trial consisted of a fixation display, a search display, and a feedback display (see Figure 1). All stimuli were presented on a black background.

The fixation display showed a white cross (subtending 0.5° visual angle) inside a white circle (1.5°) in the center of the display. A small yellow dot also appeared to show the participant's gaze location. After gaze had been registered inside the circle for 700 ms, the dot disappeared and the circle and cross turned yellow for 300 ms. If 700 ms of gaze time was not detected in the fixation circle, the trial proceeded as usual after 4,000 ms.

After a blank interval of 150 ms, the search display appeared: five circles and one diamond (target). These shapes (each 2.3° × 2.3°) were spaced equally around the screen center at 5.1° eccentricity. Depending on the trial type, either one or two of the circles were colored blue, green, or orange (CIE x/y coordinates: blue = .192/.216; green = .302/.538; orange = .492/.445); we refer to these colored circles as distractors. The assignment of colors to the roles of HV, LV, and NV distractors was counterbalanced

Figure 1
Example Trial of the Search Task



Note. Participants began each trial by fixating on a central cross. A search display then appeared, and participants' task was to look at the diamond-shaped target as quickly and directly as possible. The color of a distractor in the display signaled the number of points that were available for making a rapid response. A subsequent feedback screen showed the number of points won. See the online article for the color version of this figure.

across participants. All other shapes—including the target—were gray (.327/.400). The luminance of gray (~8.3 cd/m^2) was lower than the other colors (~24.5 cd/m^2).

Participants' task was to move their eyes to the diamond target as quickly and directly as possible. A response was registered when 100 ms of gaze dwell time had accumulated within a region (diameter 3.1°) surrounding the target. Rewards were earned for response times below 800 ms. If no response was recorded before 2,000 ms elapsed the trial timed out. Following protocols used in our previous research (Le Pelley et al., 2015; Pearson et al., 2015), an additional larger region (diameter 5.1°) was defined around the distractor. If any gaze sample was recorded within this distractor region, the participant's gaze was considered to have been on the distractor on that trial.

Immediately on a response being registered, or after a timeout, the search display was replaced by the feedback display. If the response time was below 800 ms, feedback displayed the number of points earned, otherwise, feedback stated "TOO SLOW: You could have won X points," where X was the number of points available on that trial. Feedback appeared for 1,300 ms, followed by a 1,200-ms blank intertrial interval, after which the next trial began.

The search task comprised 16 blocks of 42 trials. For the first eight blocks, the search display featured a single colored distractor in either the HV color (hereafter referred to as HV trials), the LV color (LV trials), or the NV color (NV trials), with equal numbers of each in random order. On these "single-distractor" trials, distractor color signaled the magnitude of reward available (see Table 1).

For trial types with uncertain rewards, a randomly chosen half of trials of that type in each block were assigned to each possible outcome level (e.g., for HV trials, seven trials per block had an available reward of 0 points and seven trials had an available reward of 100 points).

In the second half of the search task, alongside single-distractor trials as described above, we introduced a small number of trials featuring two distractors in the search display: a HV and LV distractor (HV–LV trials), a HV and NV distractor (HV–NV trials), or a LV and NV distractor (LV–NV trials). These "double-distractor" trials were designed to place different types of distractors in direct competition for attentional priority (cf., Le Pelley et al., 2019; Pearson et al., 2016). The available reward on double-distractor trials was always 50 points.[3] Each of the latter eight blocks of the search task contained 12 instances of each type of single-distractor trial intermixed with two of each type of double-distractor trial, in random order.

Target location was determined randomly in each trial. In single-distractor trials, the location of the distractor was pseudorandom, with the constraint that it never appeared directly opposite the target. On double-distractor trials, the location of the first distractor was determined in the same way, and the second was positioned equidistant from the target (i.e., if the first distractor was one location clockwise from the target, the second distractor was one location anticlockwise from the target).

Choice Task. A subsequent choice task assessed participants' explicit knowledge of the expected value associated with each distractor. In each trial, a pair of search displays appeared on either side of the screen, each containing a single colored distractor. Participants were told they would be credited with the number of points available for 50 trials with the chosen distractor, so they should select the display containing the color that would allow them to earn more points. Participants made choices for each of the three pairs of distractor colors (HV vs. LV, HV vs. NV, LV vs. NV) four times, in random order, with the left/right presentation order of the two options counterbalanced over the four presentations of each pair. After each choice, feedback stated "Points for 50 trials with this color have been added to your total," but did not reveal the number of points added.

Estimation Task. In an estimation task, participants saw an example search display featuring a single distractor and were asked to estimate the average number of points that they could win on that trial, by clicking a visual analog scale ranging from 0 to 100 points, with markers at 10-point intervals. Participants provided one estimate for each of the three distractor colors in random order.

Procedure

Participants were told their task was to look at the diamond-shaped target on each trial of the search task, that they could earn reward points depending on how quickly and accurately they responded, and that they would receive a bonus (typically between AU$7 and AU$12) at the end of the experiment based on how many points they earned. Instructions stated that the color of the distractor in the search display signaled how many points were available on each trial, but participants were not told the number of points signaled by each color. It was stressed that participants' task was to look at the diamond target to earn points and that this target would never be colored—so the best strategy was to ignore the colored circles and look directly at the target.

Participants took a short break after each block of the search task. Following the search task, participants were reminded that the number of points available on each search trial had been determined by the color of the colored circle in the display and were told they would be tested on what they had learned about the different colors of circles. They then completed the choice task and the estimation task.

Data Analysis

Following previous protocols (e.g., Le Pelley et al., 2019), data from the first two trials of each block were discarded, along with trials in which the search display timed out with no response to the target registered within 2,000 ms (2.09% of all trials), and trials in which valid gaze location was registered in less than 25% of recorded samples (0.42% of all trials). Data for each trial type were then averaged across the search task. Greenhouse–Geisser corrected degrees of freedom are reported where appropriate. When a conclusion is drawn regarding a null result, we report the results of a Bayesian t test conducted using the BayesFactor package with the default Jeffreys–Zellner–Siow prior (Morey & Rouder, 2022).

Transparency and Openness

For all experiments reported in this article, we report how we determined our sample size, any data exclusions, as well as all manipulations and measures. Data, experiment, and analysis code are available at https://osf.io/hra94/. Analyses were conducted using R, Version 4.2.2 (R Core Team, 2022).

Results

Search Task

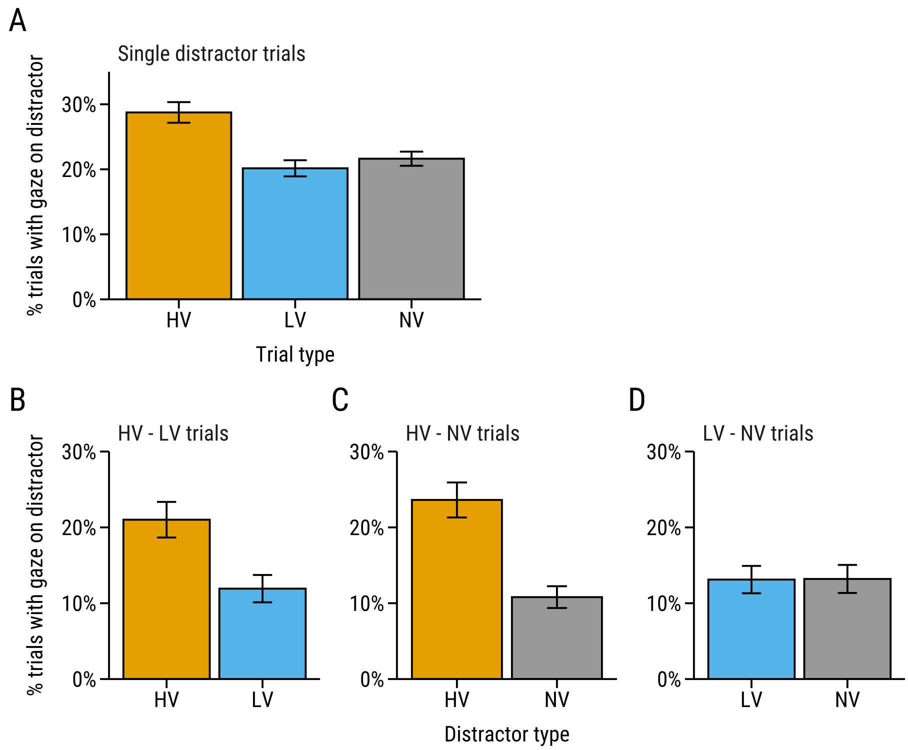
The dependent variable was the proportion of trials in which participants looked at the distractor for each trial type, averaged across blocks of the task (see the online supplemental materials for analyses of data from all experiments including block as a factor). We first assessed performance on single-distractor trials (see Figure 2A). A one-way repeated-measures analysis of variance (ANOVA) revealed a significant main effect of distractor type, $F(1.65, 49.65) = 12.1$, $p < .001$, $\eta_p^2 = 0.287$. Bonferroni-corrected pairwise t tests indicated that, critically, participants were significantly more likely to look at the distractor on HV trials than LV trials, $t(30) = 4.00$, $p = .001$, $d_z = 0.71$. Participants were also significantly more likely to look at the distractor on HV trials than NV trials, $t(30) = 3.60$, $p = .003$, $d_z = 0.65$. There was no significant difference between LV and NV trials, $t(30) = 1.05$, $p = .900$, $d_z = 0.19$, $BF_{01} = 3.14$.

Figure 2B–D shows the proportion of double-distractor trials in which participants looked at each distractor for each trial type. Consistent with the pattern from single-distractor trials, participants were significantly more likely to look at the HV distractor than the LV distractor on HV–LV trials, $t(30) = 2.73$, $p = .010$, $d_z = 0.49$,

[3] Taking into account the outcomes experienced on double-distractor trials would change the statistics for expected value, entropy and variance associated with each distractor as listed in Table 1. However, double-distractor trials were in a small minority (∼7% of all trials), so their impact on reward statistics was slight. More importantly, the resulting changes to reward statistics would not change the ordinal patterns (e.g., entropy and expected value would still be matched for HV and LV distractors; HV distractors would still have higher variance than LV distractors, etc.).

Figure 2

Proportion of Trials in Which Participants Looked at the Distractor in Experiment 1



Note. Panel A shows data from single-distractor trials with an HV, LV, or NV distractor; panels B–D show data from double-distractor trials: HV versus LV (panel B); HV versus NV (panel C); and LV versus NV (panel D). Error bars show within-subjects standard error of the mean (Morey, 2008). HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

and more likely to look at the HV than the NV distractor on HV–NV trials, $t(30) = 4.63$, $p < .001$, $d_z = 0.83$. On LV–NV trials there was no significant bias, $t(30) = 0.04$, $p = .969$, $d_z = 0.01$, $BF_{01} = 5.22$.

Choice Task

For each choice type used in the choice task (HV vs. LV, HV vs. NV, LV vs. NV), the selection of the first-listed option (e.g., selection of the HV distractor on HV vs. LV trials) was coded as 1, and selection of the second-listed option (e.g., selection of LV on HV vs. LV trials) was coded as −1. So across the four selections made for each choice type, the resulting mean choice response score for each participant could take only five values (−1, −0.5, 0, 0.5, or 1) and so data did not meet assumptions for parametric analysis. Consequently, we analyzed these data (see Figure 3A) via one-sample Wilcoxon signed-rank tests to compare mean choice scores against zero (no bias in choice). There was no significant bias toward the choice of one type of distractor over the other for any of the choice types: HV versus LV, $W = 175.5$, $Z = 0$, $p = 1.000$; HV versus NV, $W = 143.5$, $Z = 0.18$, $p = .859$; LV versus NV, $W = 159.0$, $Z = 0.08$, $p = .933$.

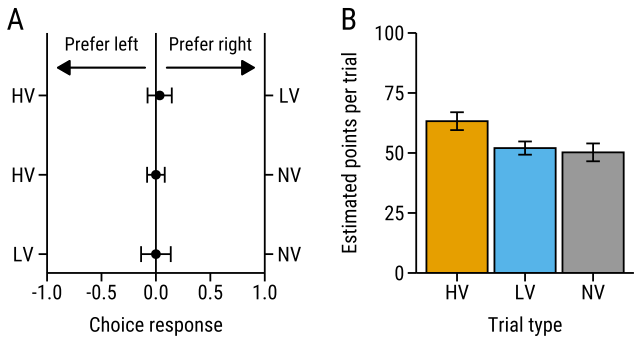
Estimation Task

Figure 3B shows participants' value estimates for each distractor. One-way ANOVA revealed a significant effect of distractor type, $F(1.78,\ 47.98) = 4.23$, $p = .024$, $\eta_p^2 = 0.135$. Follow-up Bonferroni-corrected *t* tests revealed that the pattern of higher estimates for the HV distractor than the LV distractor did not reach significance, $t(27) = 2.55$, $p = .051$, $d_z = 0.48$, $BF_{01} = 0.34$, nor did the trend toward higher estimates for the HV versus NV distractor, $t(27) = 2.30$, $p = .087$, $d_z = 0.44$, $BF_{01} = 0.53$. There was no significant difference for the LV versus NV distractor, $t(27) = 0.41$, $p = 1.000$, $d_z = 0.08$, $BF_{01} = 4.62$.

Discussion

The critical finding of Experiment 1 is that participants' gaze was more likely to be captured by a distractor associated with high reward variance than a distractor associated with lower reward variance, even though these distractors were matched in expected value and entropy. This pattern was demonstrated when the distractors were color singletons, and when both distractors appeared simultaneously such that they were in direct competition with one another. These findings are consistent with the idea that attentional priority is influenced by outcome variance, independent of entropy and expected value. Notably, data from the double-distractor trials suggest that the impact of reward uncertainty was not simply due to a weakening of overall attentional control. If the attentional set for the target was weaker on trials featuring the HV distractor, we would expect to see no difference in the percentage of trials with gaze on each distractor

Figure 3
Data From Knowledge Tests in Experiment 1



Note. Markers in panel A show mean choice response scores for each pair of distractors in the choice task: HV versus LV (top); HV versus NV (middle); LV versus NV (bottom). The vertical line at 0 represents indifference between the two options; negative scores indicate a preference for the distractor type shown on the left *y*-axis, and positive scores indicate a preference for the distractor type shown on the right *y*-axis. Panel B shows participants' mean estimates of the average point value associated with each distractor. Error bars show within-subjects standard error of the mean. HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

on HV–LV trials, as a weaker attentional set would lead to a general increase in capture by both of the physically salient distractors present in the search display. By contrast, we found a specific increase in capture by the HV distractor on these trials, suggesting that the experienced reward uncertainty causes a specific increase in the HV distractor's attentional priority (cf., Pearson et al., 2016).

We also found that participants were more likely to look at HV than NV distractors. This finding replicates previous findings of UMAC (Cho & Cho, 2021; Le Pelley et al., 2019) and could be a consequence of the greater variance or greater entropy associated with the HV distractor (or both). It is notable, however, that there was no significant difference in capture by the LV and NV distractors in either single- or double-distractor trials. This finding was unexpected, given that the LV distractor was associated with both greater entropy and variance than the NV distractor (see Table 1). However, the function mapping entropy and/or variance to attentional priority is currently unknown, and it is possible that differences between LV and NV distractors were too small for a reliable difference in attention to be observed. We return to this issue in the General Discussion.

All distractors in Experiment 1 had equal expected value, and when participants were asked to choose the distractor they thought would provide the larger pay-off in the choice task, choices were (as expected) equally split between different distractor types. However, data from the estimation task provide some evidence to suggest that participants' perceptions of distractor values varied: we found a significant effect of distractor type on estimates, with a trend toward higher estimates for the HV than LV or NV distractors. Given that the corresponding pairwise contrasts did not reach significance when corrected for multiple comparisons—combined with the lack of preference in the choice task—we should not give this possibility undue emphasis. However, it does suggest a potential alternative explanation for the results of Experiment 1: if participants (incorrectly) perceived that the HV distractor was associated with a higher expected value than the LV/NV distractors, then the attentional priority of this HV distractor may reflect the operation of a process modulated by (subjective) expected value, rather than outcome variance per se.

Experiment 2

In Experiment 2, we addressed this concern by increasing the expected value of the LV distractor relative to the HV and NV distractors, thus placing outcome variance and expected value in opposition. Whereas in Experiment 1, the LV distractor had signaled 40 or 60 points, in Experiment 2, it now signaled 80 or 90 points—yielding an expected value (85) that was greater than that of the HV/NV distractors (50); see Table 2. Consequently, any influence of expected value on attention would favor greater capture by the LV distractor than the HV distractor. If we were nevertheless to observe an attentional bias to the HV distractor over the LV distractor under these conditions, that would provide potent evidence consistent with an influence of outcome variance on attentional priority.

Method

A total of 36 UNSW Sydney students (11 man/male, 25 woman/female, age $M = 21.1$ years, $SD = 5.98$) participated for course credit and received a monetary bonus depending on their performance ($M =$ AU\$11.51, $SD =$ AU\$0.52). Apparatus, stimuli, design, and procedure were as in Experiment 1, except for the magnitude of reward available on LV trials, which was now either 80 or 90 points (with equal probability). Data analysis was as for Experiment 1. After excluding the first two trials after each break, we discarded timeouts (0.58% of trials), and trials with less than 25% of valid gaze samples (0.29%).

Results

Search Task

Figure 4A shows gaze data from single-distractor trials. One-way ANOVA revealed a significant effect of distractor type, $F(1.67, 58.51) = 6.01$, $p = .007$, $\eta_p^2 = 0.147$. Critically, Bonferroni-corrected contrasts revealed that participants were significantly more likely to look at the HV than the LV distractor, $t(35) = 3.18$, $p = .009$, $d_z = 0.53$. As in Experiment 1, participants were more likely to look at the HV than the NV distractor; this difference did not reach (corrected) two-tailed significance, $t(35) = 2.22$, $p = .098$, $d_z = 0.37$, though we note that as a direct replication of the pattern in Experiment 1, it would be significant at a one-tailed level. There was no significant difference between the LV and NV distractors, $t(35) = 0.95$, $p = 1.000$, $d_z = 0.16$, $BF_{01} = 3.69$.

Figure 4B–D shows the proportion of double-distractor trials in which participants looked at each distractor. Consistent with the

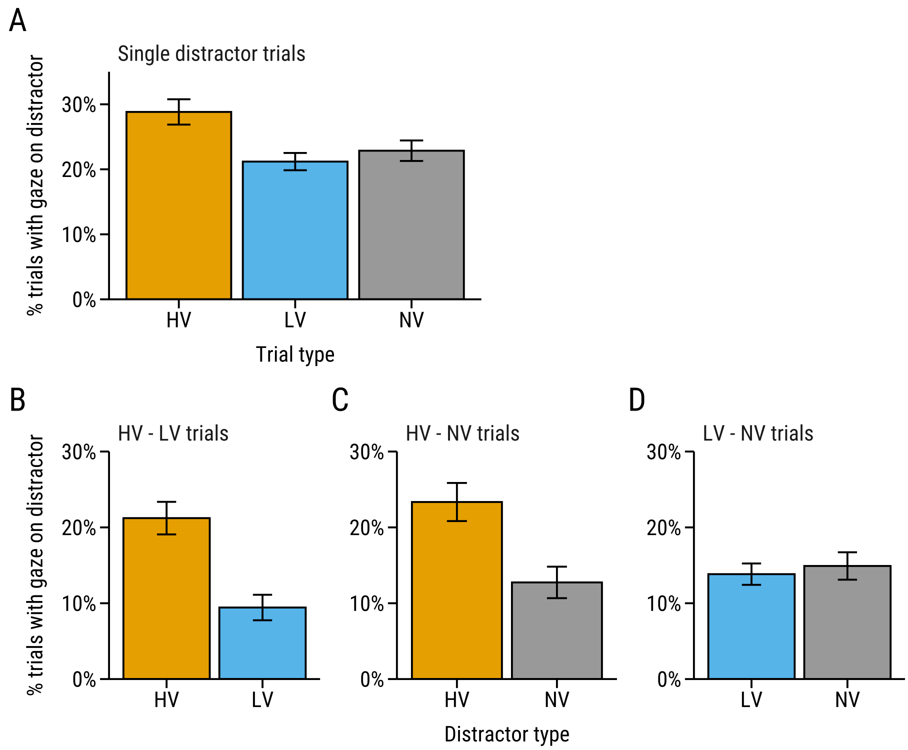
Table 2
Outcome Parameters for Single-Distractor Trials in Experiment 2

Distractor type	Available reward	Reward probability	Expected value	Entropy (bits)	Variance
HV	0/100	.5/.5	50	1	2,500
LV	80/90	.5/.5	85	1	25
NV	50	1	50	0	0

Note. HV = high variance; LV = low variance; NV = no variance.

Figure 4

Proportion of Trials in Which Participants Looked at the Distractor in Experiment 2



Note. Panel A shows data from single-distractor trials featuring an HV, LV, or NV distractor; panels B–D show data from double-distractor trials: HV versus LV (panel B); HV versus NV (panel C); and LV versus NV (panel D). Error bars show within-subjects standard error of the mean. HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

data from single-distractor trials, participants were significantly more likely to look at the HV distractor than the LV distractor on HV–LV trials, $t(35) = 3.64$, $p < .001$, $d_z = 0.61$, and were more likely to look at the HV than the NV distractor on HV–NV trials, $t(35) = 2.73$, $p = .009$, $d_z = 0.46$. On LV–NV trials, there was no significant bias, $t(35) = 0.44$, $p = .662$, $d_z = 0.07$, $BF_{01} = 5.10$.

Choice Task

Figure 5A shows the mean choice response scores for each choice type in the choice task. One-sample Wilcoxon signed-rank tests against zero (no bias) revealed that participants' choices showed a significant bias toward the LV distractor over the HV distractor, $W = 194.5$, $Z = 2.05$, $p = .040$, and toward the LV distractor over the NV distractor, $W = 42$, $Z = 5.05$, $p < .001$—consistent with the objectively higher expected value associated with the LV distractor in Experiment 2. There was no significant bias in the choice between the HV and NV distractors, $W = 198$, $Z = 0.74$, $p = .459$.

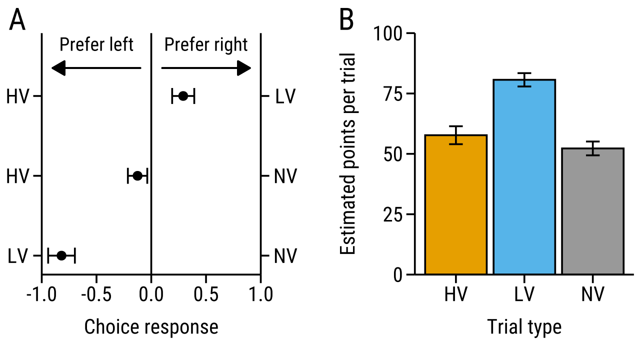
Estimation Task

Figure 5B shows participants' value estimates for each distractor. ANOVA revealed a significant effect of distractor type, $F(1.72, 60.37) = 23.01$, $p < .001$, $\eta_p^2 = .397$. Consistent with the higher (experienced) expected value of LV trials, Bonferroni-corrected contrasts revealed significantly higher value estimates for LV trials than HV trials, $t(35) = 4.77$, $p < .001$, $d_z = 0.79$, and NV trials, $t(35) = 8.24$, $p < .001$, $d_z = 1.37$. There was no significant difference in value estimates for HV and NV trials, $t(35) = 1.11$, $p = .821$, $d_z = 0.19$, $BF_{01} = 3.16$.

Discussion

In Experiment 2, participants' gaze was again more likely to be captured by a distractor associated with high reward variance than a distractor associated with lower variance, in both single- and double-distractor trials. Critically, this was the case even though the expected value of the HV distractor was lower than the LV distractor—and participants had clearly learned this difference in expected values, with an overt preference for simulated rewards from LV trials over HV trials in the choice task, and higher value estimated for LV than HV trials in the estimation task. Earlier we raised the possibility that the attentional bias toward the HV distractor observed in Experiment 1 may have reflected an influence of a difference in (perceived) expected value. This possibility is ruled out in Experiment 2 since the attentional bias to the HV distractor over the LV distractor was in the opposite direction to the difference in (objective and perceived) expected value. Rather, these results are in line with the idea that outcome variance has a direct influence on

Figure 5
Data From Knowledge Tests in Experiment 2



Note. Markers in panel A show mean choice response scores for each pair of distractors in the choice task: HV versus LV (top); HV versus NV (middle); LV versus NV (bottom). The vertical line at 0 represents indifference between the two options; negative scores indicate preference for the distractor type shown on the left *y*-axis, and positive scores indicate preference for the distractor type shown on the right *y*-axis. Panel B shows participants' mean estimates of the average point value associated with each distractor. Error bars show within-subjects standard error of the mean. HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

attentional priority that is separate from, and—in this case at least—more potent than the influence of expected value.

Once again, we did not observe a difference in attentional capture by the LV and NV distractors, even though the LV distractor was associated with greater expected value, outcome variance, and entropy than the NV distractor. This result was again unexpected: even leaving aside the influence of uncertainty, the influence of expected value on attention is well established (Anderson, 2016; Pearson et al., 2022; Watson, Pearson, Wiers, et al., 2019). Yet, in Experiment 2, we found that gaze was no more likely to be directed to the (high expected value) LV distractor than the (low expected value) NV distractor. This finding cannot be easily reconciled with an account in which attentional priority is increased by independent and additive influences of expected value and outcome variance since both of these factors should augment the priority of the LV distractor relative to the NV distractor.

One potential explanation for this pattern of results appeals to a refined version of the information-gain account, in which attentional priority reflects a trade-off between drives to gather information to reduce current uncertainty and to gather information about the most desirable outcomes (Gottlieb & Oudeyer, 2018; Sharot & Sunstein, 2020). Recent findings suggest that people prefer to inspect sources of information that will resolve less uncertainty, so long as the information provided by those sources is related to more desirable outcomes (Kobayashi et al., 2019; Rischall et al., 2023). In other words, people will seek out and "savor" advance information about a desirable outcome, even if doing so means that they will have more total uncertainty about future events (cf., Iigaya et al., 2016). By this account, participants in Experiments 1 and 2 may have been attending to the HV distractor not because this distractor was associated with higher-variance outcomes per se, but because doing so allowed them to "savor" the possibility that they would potentially receive a highly desirable 100-point outcome (the maximum reward available in the task context: see also Ludvig et al., 2014, 2015). By contrast, neither the LV nor NV distractor was ever associated with the 100-point outcome, so the attentional priority of these distractors would not be increased. This "savoring" account could also explain the standard value-modulated attentional capture effect: a high-value distractor may be more likely to capture attention than a low-value distractor because attending to the high-value distractor allows the participant to "savor" information about the desirable outcome that it signals, which is typically the maximum outcome available in the experiment (e.g., Anderson & Halpern, 2017; Failing et al., 2015; Le Pelley et al., 2015; Pearson et al., 2015).

Experiment 3

Experiment 3 tested this alternative account by increasing the value of the larger reward outcome associated with the LV distractor to 100 points: whereas in Experiment 2, the LV distractor signaled 80 or 90 points, in Experiment 3, it signaled 70 or 100 points. As a result, both the HV and LV distractors were associated with the maximum-value outcome on an equal proportion (50%) of the trials in which they were presented (see Table 3). If attentional priority reflects a trade-off between seeking information to reduce uncertainty and seeking information about the most desirable outcomes, then we would expect (if anything) greater capture by the LV distractor than the HV distractor—since attending to the LV distractor would give the same opportunity to "savor" the possibility of receiving 100 points, while also allowing participants to make more accurate predictions about the range of rewards they could potentially receive. Alternatively, if attentional priority is modulated by outcome variance (over and above any effect of savoring information about the maximum-value outcome) then we would expect a pattern of greater capture by the HV distractor compared to the LV distractor, as in Experiments 1 and 2.

Method

As a consequence of increasing the value of the larger reward outcome associated with the LV distractor, while maintaining its expected value (85 points), the variance of the LV distractor in Experiment 3 was increased relative to Experiment 2 (Var(LV) = 225 versus 25). As a result, we anticipated a smaller effect size for the critical comparison between the HV and LV distractors in Experiment 3. We therefore (approximately) doubled our sample size, for a total of 60 participants (17 man/male, 42 woman/female, one preferred not to answer, $M_{\text{age}} = 20.4$ years, $SD = 5.33$); all were UNSW students, with 52 participating for course credit, and eight for payment of AU$30. All participants received an additional performance-based bonus (M = AU$11.37, SD = AU$0.59). Apparatus, stimuli, design, and procedure were as in Experiments 1 and 2, except

Table 3
Outcome Parameters for Single-Distractor Trials in Experiment 3

Distractor type	Available reward	Reward probability	Expected value	Entropy (bits)	Variance
HV	0/100	.5/.5	50	1	2,500
LV	70/100	.5/.5	85	1	225
NV	50	1	50	0	0

Note. HV = high variance; LV = low variance; NV = no variance.

that the reward on LV trials was now either 70 or 100 points (with equal probability).

As we anticipated smaller effect sizes for the key contrasts of interest, we also limited our data analysis to a set of planned comparisons. On single-distractor trials, we conducted paired *t* tests for HV trials versus LV trials, and LV trials versus NV trials. On double-distractor trials, we conducted paired *t* tests comparing capture by each of the distractors presented on each trial type. All other aspects of the data analysis were as for Experiments 1 and 2. After excluding the first two trials after each break, we discarded timeouts (0.82% of trials), and trials with less than 25% of valid gaze samples (0.07%).

Results

Search Task

Figure 6A shows gaze data from single-distractor trials. Planned *t* tests revealed that participants were significantly more likely to look at the distractor on HV trials compared to LV trials, $t(59) = 2.17$, $p = .034$, $d_z = 0.28$. There was no significant difference between LV and NV trials, $t(59) = 0.17$, $p = .863$, $d_z = 0.02$, $BF_{01} = 6.98$.

Figure 6B–D shows the proportion of double-distractor trials in which participants looked at each type of distractor. As for single-distractor trials, participants were more likely to look at the HV distractor than the LV distractor on HV–LV trials, but here this comparison did not reach significance, $t(59) = 1.86$, $p = .067$, $d_z = 0.24$. Participants were significantly more likely to look at the HV distractor than the NV distractor on HV–NV trials, $t(59) = 2.47$, $p = .016$, $d_z = 0.32$. Notably, and in contrast to the findings of Experiments 1 and 2, there was also a significant gaze bias toward the LV distractor over the NV distractor on LV–NV trials, $t(59) = 2.64$, $p = .010$, $d_z = 0.34$.

Choice Task

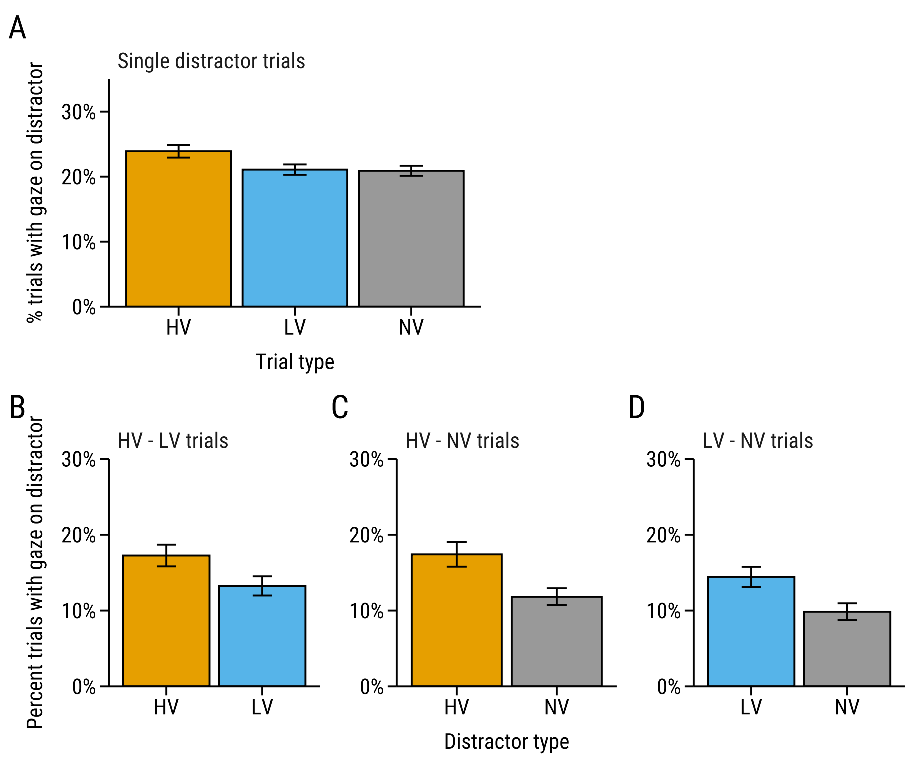
Figure 7A shows choice response scores for each choice type in the choice task. Participants showed a significant bias toward the LV distractor over the HV distractor, $W = 184.0$, $Z = 5.38$, $p < .001$, and toward the LV distractor over the NV distractor, $W = 62.5$, $Z = 6.40$, $p < .001$—consistent with the objectively higher expected value associated with the LV distractor. There was also a significant bias toward the NV distractor over the HV distractor, $W = 389.5$, $Z = 2.66$, $p = .008$.

Estimation Task

Figure 7B shows value estimates for each distractor. ANOVA revealed a significant effect of distractor type, $F(1.55, 91.43) = 27.4$, $p < .001$, $\eta_p^2 = .317$. Bonferroni-corrected contrasts revealed that the pattern of participants' estimates corresponded to the

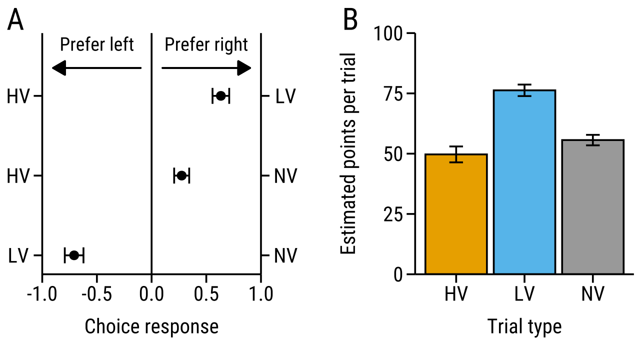
Figure 6

Proportion of Trials in Which Participants Looked at the Distractor in Experiment 3



Note. Panel A shows data from single-distractor trials featuring an HV, LV, or NV distractor; panels B–D show data from double-distractor trials: HV versus LV (panel B); HV versus NV (panel C); and LV versus NV (panel D). Error bars show within-subjects standard error of the mean. HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

Figure 7
Data From Knowledge Tests in Experiment 3



Note. Markers in panel A show mean choice response scores for each pair of distractors in the choice task: HV versus LV (top); HV versus NV (middle); LV versus NV (bottom). The vertical line at 0 represents indifference between the two options; negative scores indicate preference for the distractor type shown on the left *y*-axis, and positive scores indicate preference for the distractor type shown on the right *y*-axis. Panel B shows participants' mean estimates of the average point value associated with each distractor. Error bars show within-subjects standard error of the mean. HV = high variance; LV = low variance; NV = no variance. See the online article for the color version of this figure.

expected value of the trial types, with higher value estimates for LV trials than either HV trials, $t(59) = 6.10$, $p < .001$, $d_z = 0.79$, or NV trials, $t(59) = 8.02$, $p < .001$, $d_z = 1.03$. There was no significant difference in the value estimates for HV and NV trials, $t(59) = 1.44$, $p = .466$, $d_z = 0.19$, $BF_{01} = 2.67$.

Discussion

In Experiment 3, participants' gaze was once again more frequently captured by a distractor that signaled HV outcomes than a distractor that signaled lower-variance outcomes, even though the LV distractor had a higher expected value. We previously proposed an alternative account of the findings from Experiments 1 and 2, wherein the heightened attentional priority of the HV distractor reflected a drive to "savor" information about the most desirable outcome available in the task context, rather than its outcome variance. The results of Experiment 3 rule out this account since the HV and LV distractors were equally paired with the maximum-value outcome. Instead, these findings suggest that outcome variance independently and directly modulates attentional priority, separate from any influences of expected value, entropy, and association with the maximum-value outcome.

The findings of Experiment 3 present some inconsistencies with those of Experiments 1 and 2 that merit further consideration. First, the difference in capture by the HV versus LV distractors on single-distractor trials had a smaller effect size in Experiment 3 ($d_z = 0.28$) compared to Experiment 1 ($d_z = 0.71$) and Experiment 2 ($d_z = 0.53$), and this difference did not reach two-tailed significance on double-distractor trials. A second inconsistency was that gaze was more likely to be captured by the LV distractor than the NV distractor on double-distractor trials, a pattern not observed in Experiments 1 and 2, or on single-distractor trials of Experiment 3. Taken together, these findings suggest that the attentional priority of the LV distractor was increased in Experiment 3, compared to Experiments 1 and 2. This may be because the outcome variance associated with the LV distractor was higher in Experiment 3 (Var = 225) than in Experiment 1 (100) or Experiment 2 (25): a consistent finding of the current research is that priority is influenced by outcome variance. An alternative possibility is that the greater priority of the LV distractor in Experiment 3 stems from its pairings with the maximum-value outcome. We return to this topic in the General Discussion.

General Discussion

The three experiments reported here investigated the influence of outcome variance—as a parameter of uncertainty—on attentional prioritization of reward-related stimuli. Across all three experiments, participants were more likely to make erroneous saccades toward a distractor associated with high outcome variance, than a distractor associated with lower outcome variance. This was shown when the expected values of the distractors were matched (Experiment 1), when the expected value of the HV distractor was lower than that of the LV distractor (Experiment 2), and when the HV and LV distractors were matched for their association with the maximum-value outcome (Experiment 3). Importantly, the entropy associated with HV and LV distractors was also matched in each experiment. Together these findings suggest that outcome variance plays a specific role in shaping automatic attentional prioritization, independent of entropy, expected value, and association with the maximum-value outcome.

Previous research has demonstrated that selection history is modulated by experience of uncertainty: the attentional priority of a stimulus is influenced by experience of uncertainty in the outcomes with which it is paired, such that stimuli associated with relatively high uncertainty are more likely to capture attention than stimuli associated with lower (or no) uncertainty (Cho & Cho, 2021; Le Pelley et al., 2019). This phenomenon of UMAC conflicts with the idea that a primary determinant of attention is the drive to gain information to minimize current uncertainty (Gottlieb & Oudeyer, 2018; Gottlieb et al., 2020), because such accounts anticipate greater attention to cues that allow for more accurate predictions to be made about future events: that is, cues that are associated with lower outcome uncertainty (equivalently, cues that are more diagnostic).

By contrast, the findings of UMAC are more consistent with the concept of "attentional exploration," wherein uncertainty-related stimuli are prioritized in an attempt to learn about their true predictive status and thereby reduce uncertainty when these stimuli are encountered again in the future (Beesley et al., 2015; Le Pelley et al., 2016; Pearce & Hall, 1980). Of course, in a typical UMAC procedure outcomes are delivered probabilistically, and hence learning cannot improve the accuracy of predictions—nevertheless, exploration-based accounts see priority as driven by the potential for learning to reduce future uncertainty. More specifically, these models propose that attentional priority is shaped by prediction error (cf., Dayan et al., 2000; Esber & Haselgrove, 2011; Le Pelley, 2004; Pearce & Hall, 1980), which is influenced not only by outcome entropy (related to the number of distinct outcomes that can occur) but also by the magnitude of the discrepancy between expectation and observation—which implicates the identity of the outcome (i.e., whether it is larger or smaller than expected). The current findings provide evidence consistent with this latter idea, demonstrating that priority is not merely a product of the number of qualitatively distinct outcomes that can occur (cf., Ju & Cho, 2023), but is also a quantitative function of outcome variance: that is, greater outcome variance results in larger prediction errors, which result in increased attention to the cue.

Uncertainty Versus Expected Value

The observation of greater attention to the HV (lower value) distractor over the LV (higher value) distractor in Experiments 2 and 3 might be taken to suggest that the expected value plays no role in the determination of attentional priority. However, we know from substantial prior research that attention can be influenced by expected value independently of uncertainty (e.g., Anderson & Halpern, 2017; Anderson et al., 2011; Garner et al., 2021, 2022; Le Pelley et al., 2015; Pearson & Le Pelley, 2020; Pearson et al., 2015, 2016, 2020; Watson, Pearson, Chow, et al., 2019; Watson, Pearson, Most, et al., 2019). For instance, in Experiment 3 of Le Pelley et al. (2015), participants were more likely to look at a distractor paired with a high-value reward over a distractor paired with a low-value reward when both distractors were associated with no reward uncertainty (i.e., each distractor was perfectly predictive of its associated reward). Moreover, the influence of expected value on attentional capture is not restricted to situations in which rewards are fixed. For example, a distractor paired with a high reward on 80% of trials and a low reward on 20% of trials captures attention over a distractor with the reverse reward contingency (i.e., high reward: 20%, low reward: 80%; e.g., Anderson & Halpern, 2017; Anderson et al., 2011). The current findings suggest that the impact of uncertainty on attention is more potent than that of the (opposing) difference in expected value. Future research will be needed to gain a more complete understanding of the ways in which the influences of expected value and uncertainty interact—and potentially compete—in the calculation of overall attentional priority.

UMAC as a Function of Entropy and Variance

Our study focused on variance as a contributor to prediction error in the context of attentional exploration. Recent work by Ju and Cho (2023) took a complementary approach, demonstrating that UMAC is also mediated, at least in part, by entropy. One of their experiments compared attentional capture by two distractors associated with equal levels of outcome variance, but different levels of entropy—and found evidence of greater capture by the high-entropy stimulus. Taken together with the current findings, the implication is that both entropy and variance—two critical components of prediction error—act to modulate attentional priority.

That said, our findings conflict with those of Ju and Cho (2023) in some regards. Their study was primarily concerned with assessing the influence of entropy on attention, but one of their experiments (Experiment 4) aimed to test the possible influence of variance by comparing two distractors associated with different levels of outcome variance but with equal entropy and expected value (conceptually similar to our Experiment 1). In contrast to the current findings, Ju and Cho found no significant effect of variance under these conditions. The reasons for this discrepancy are unclear, but several points of difference are worth noting here. First, Ju and Cho used a two-phase procedure (see Pearson et al., 2022; Rusz et al., 2020) in which the critical reward-signaling colors defined the targets of search during an initial training phase, before becoming distractors in a subsequent test phase—in contrast to the current one-phase procedure in which the reward-signaling colors were never the search target and were distractors throughout. It has been suggested that this one-phase procedure may be more sensitive to detecting the effects of reward on attention (Anderson & Halpern, 2017). Second, while Ju and Cho equated the objective expected value of the critical stimuli, they did not assess whether there was a difference in participants' subjective perception of these values (cf., the current Experiment 1), so it is possible that the effect of a difference in perceived value opposed an effect of variance in their study. Finally, the difference in variance involved in their study (180 points) was much smaller than in the current experiments (2,400 points in Experiment 1; 2,475 in Experiment 2; 2,275 in Experiment 3). Hence Ju and Cho's null finding may reflect a procedure that was not sufficiently sensitive to detect a significant difference created by a relatively small difference in variance. Future research will be required to establish the reason for this discrepancy.

Comparison of Capture by LV and NV Distractors

One unexpected aspect of our findings relates to the contrast of data from the LV and NV conditions. In Experiments 1 and 2, we found no significant difference in attention to LV versus NV distractors. This is surprising because (for example) in Experiment 2 the LV distractor had both greater variance and expected value than the NV distractor. We know from prior research that value modulates attention in this task (e.g., Le Pelley et al., 2019; Pearson & Le Pelley, 2020; Pearson et al., 2016; Watson et al., 2020), and if variance also modulates attention then we would naturally expect greater capture by the LV distractor than the NV distractor. One possibility is that the differences in variance and value between LV and NV distractors were not large enough to sustain a significant difference in priority between these stimuli. In this regard, it is notable that the difference in expected value in the current experiments was substantially smaller than in the studies cited above as demonstrating effects of value on attention. Moreover, previous studies investigating the influence of entropy on attention found no increase in capture for a distractor that was associated with a small increase in entropy (Ju & Cho, 2023), suggesting that there may be some minimum threshold increase of uncertainty required to demonstrate a UMAC effect. Further evidence in line with this idea comes from Experiment 3: when the variance of the LV distractor was increased, we did find that the LV distractor captured attention over the NV distractor when both stimuli appeared in the same search display. However, this pattern of results may have been a consequence of the association between the LV distractor and the maximum-value outcome in Experiment 3, rather than this (relatively small) increase in variance. An account in which the attentional priority of a stimulus is increased as a consequence of its association with the maximum-value outcome, rather than its expected value, could also explain the "standard" finding of greater capture by stimuli associated with high-value reward versus low-value reward. The key distinction is whether the influence of value on attentional priority is related to the long-run average of all of the outcomes that are paired with a particular stimulus, or only the "best" outcome paired with that stimulus. Unpacking these possibilities remains an avenue for future research.

Variance Versus Other Measures of Spread

Returning to the demonstrated effect of variance in the current study, we should clarify an issue of terminology. In characterizing these experiments and their findings, references to an impact of outcome "variance" should be read more as a shorthand for the concept of the spread of outcome values than as a specific, formal parameter of uncertainty. That is, variance is formally defined; however, the current data are equally amenable to a model in which priority is determined by other measures of spread that encode the value of outcome events, such as range or standard deviation (all of which could similarly be used to characterize prediction error). Future studies could investigate this issue more closely by dissociating different parameters relating to the spread of outcome values; for example, the set {0, 10, 90, 100} has higher variance than {0, 40, 60, 100}, but equal range.

Information Gain Versus Attentional Exploration

As noted earlier, demonstrations of UMAC challenge theoretical accounts arguing that the primary drive of the attentional priority system is to gather information from reliable sources to reduce current uncertainty and optimize the quality of our predictions (Gottlieb & Oudeyer, 2018; Gottlieb et al., 2020). According to these perspectives, cues that are associated with the least variable outcomes (the NV distractor in the current study) should be preferentially prioritized by the attention system, since attending to these stimuli would reduce our uncertainty and allow us to make the most reliable predictions about the outcome. However, a consistent finding of the current study is that attention was directed to the cue associated with the most variable outcome, and attending to this cue leaves maximum unresolved uncertainty about the outcome.

To successfully navigate our complex environment, it is essential that we strike a balance between exploring (investigating current unknowns so that we can build a more accurate and detailed model of the world) and exploiting (making use of existing knowledge to drive behavior that has been successful in the past). The trade-off between drives to explore and exploit is central to theories of decision-making and motivated behavior (e.g., Cohen et al., 2007; Hills et al., 2015; Mehlhorn et al., 2015; Schwartenbeck et al., 2019; Sutton & Barto, 2018). The current research joins a body of existing work in suggesting that this fundamental tension can also be observed at the level of attentional selection. That is, these studies highlight competing drives toward attentional exploration (prioritizing uncertainty-associated stimuli to reduce uncertainty in future) versus exploitation (prioritizing sources that maximize current information gain to optimize decisions). Clearly, both processes must play a role in shaping overall priority, but the factors that determine which process will ultimately govern selection are yet to be determined.

A notable point of difference between work on UMAC—consistent with attentional exploration—and research highlighting increased attentional priority for cues that resolve current uncertainty—attentional exploitation—lies in the task objectives. In the present study, and other demonstrations of UMAC (Cho & Cho, 2021; Ju & Cho, 2023; Le Pelley et al., 2019), attending to the reward-related distractor went against the goals of the task. Participants had to look at the diamond target on each trial, and any erroneous shift of attention toward the distractor would only slow their response and so reduce their likelihood of earning a reward. By setting up a scenario where participants' goals are in opposition to the selection of the distractor, we can infer that outcome variance has an automatic influence on attentional priority that is driven by selection history. That is, stimuli associated with more variable outcomes are rapidly and automatically prioritized for selection by the attention system, even when our intention is to direct attention elsewhere.

By contrast, in studies demonstrating prioritization of cues that provide greater information gain, observers were required to make a saccade to the cue in order for the task to proceed (e.g., Blanchard et al., 2015; Bromberg-Martin & Hikosaka, 2009; Foley et al., 2017; Horan et al., 2019), or there was no competing goal to direct attention elsewhere (Daddaoua et al., 2016). This raises the possibility that these previous findings reflect top-down (volitional), rather than selection-history-based (automatic) influences on attentional selection. In other words, when we are given the choice to intentionally gather information about an upcoming event, we would prefer to sample from a source that provides more reliable information and so resolves our uncertainty about what will come next. However, even when we are trying to avoid paying attention to distracting information in our environment, selection history creates a drive toward attentional exploration that acts to prioritize—and potentially drive capture by—signals of more variable outcomes.

Broader Implications and Future Directions

As noted previously, uncertainty is a fundamental feature of the environment, and the way that we interact with and attempt to minimize uncertainty is relevant to almost all areas of perception, cognition, and behavior. Having considered the significance of these findings for our understanding of attentional control, we end by discussing some of their broader implications.

Evidence from the decision-making literature has demonstrated that attended choice alternatives are more likely to be chosen than less attended alternatives (Bhatnagar & Orquin, 2022). To account for these findings, contemporary models have proposed a causal role for attention in the decision-making process, where the more attention an alternative receives, the more rapidly evidence accumulates in support of that option, and so the more likely it is to be chosen (e.g., Busemeyer & Townsend, 1993; Cavanagh et al., 2014; Krajbich, 2019; Smith & Krajbich, 2019). Recent research in this area has focused on the influence of voluntary, top-down attentional processes, arguing that we intentionally pay attention to goal-relevant stimuli to gather the information that will be most likely to influence our choice preferences (Callaway et al., 2021; Jang et al., 2021; Sepulveda et al., 2020). However, recent evidence suggests that involuntary, selection-history-based attentional biases (such as those to stimuli signaling high expected value) may play a similar role in modulating choice (Gluth et al., 2018, 2020; Itthipuripat et al., 2015; Le Pelley et al., 2023; for a recent review, see Pearson et al., 2022).

The current findings demonstrate a selection-history-driven attentional bias to stimuli associated with high uncertainty. To the extent that these rapid, involuntary attentional biases modulate choice, this may lead to a choice bias for stimuli associated with uncertain outcomes. Although we did not observe an influence of UMAC on choice trials in the current study, the choice task that we used involved only a small number of simple binary choices that were made with no time pressure, and as such was not intended to provide a rigorous test of UMAC's potential influence on choice. Future research could investigate the proposed interaction between UMAC and choice by using a more appropriate choice task design (e.g., see Gluth et al., 2018, 2020; Itthipuripat et al., 2015; Le Pelley et al., 2023) and/or by developing computational models of the influence of attention on choice (e.g., Gluth et al., 2018, 2020; Krajbich, 2019; Thomas et al., 2019).

In some contexts, choosing stimuli with highly variable outcomes may be adaptive: choosing these stimuli provides the opportunity to explore their outcomes and potentially gain a more complete understanding of their predictive status. However, involuntarily attending to and choosing stimuli associated with increased uncertainty has the potential to be counterproductive in some circumstances, such as in the context of gambling (Anselme & Robinson, 2020; Hellberg et al., 2019). Future research could explore this potential relationship between individual variability in UMAC and gambling: are those with a propensity to assign increased attentional priority to cues signaling uncertainty also more likely to engage in problematic gambling behaviors?

Outside of the gambling context, the subjective experience of uncertainty is thought to play a central role in a variety of mental health problems. Intolerance of uncertainty (IU) has been identified as a transdiagnostic risk factor for mental health, particularly anxiety disorders (Carleton, 2016). Individuals scoring high in IU are proposed to show an attentional bias to cues that signal uncertainty, which are then interpreted as threatening. In line with this idea, high IU individuals have been shown to demonstrate an attentional bias to uncertainty-related words (Fergus et al., 2013; Rogers et al., 2022), as well as heightened physiological and neural responses to uncertain threat (e.g., Morriss et al., 2015) and reward (e.g., Gorka et al., 2016; Nelson et al., 2016). However, to the best of our knowledge, no study has investigated whether individual differences in IU modulate the automatic, selection-history-driven attentional bias to cues associated with increased reward variance that was reported in this study. This remains a question to be addressed in future research.

Conclusions

In summary, previous studies have demonstrated that uncertainty modulates attentional prioritization via selection history, such that stimuli associated with uncertain reward outcomes are more likely to capture attention than stimuli associated with certain reward outcomes. The current study investigated the influence of one component of uncertainty—outcome variance—on attentional prioritization. Our results indicate that outcome variance (or the spread of outcome values more generally) has an independent and potent influence on attentional prioritization. At a higher level, our findings are inconsistent with accounts that suggest that the primary drive of visual attention is to attempt to resolve current uncertainty by exploiting reliable sources of information in the environment. Rather, our findings suggest that selection history acts to bias attention toward the exploration of currently unreliable sources of information, potentially to learn more about them and reduce future uncertainty. In doing so, these findings highlight the importance of "attentional exploration," driven by the experience of prediction error, as a fundamental component of visual information processing.

Constraints on Generality

We sampled from an undergraduate psychology student participant pool at UNSW Sydney. Participants were required to have normal or corrected-to-normal vision, including normal color vision. The general finding of increased attentional capture by more uncertain stimuli is consistent with previous findings from our lab and others (e.g., Cho & Cho, 2021; Ju & Cho, 2023; Le Pelley et al., 2019), despite differences in experimental design and stimuli. We expect that these results will be reproducible in samples taken from similar subject pools, using similar materials to those described. We have no reason to believe that the results depend on any other characteristics of the participants, materials, or context.

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Received September 25, 2023
Revision received February 24, 2024
Accepted March 7, 2024 ■