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Variability and Accessibility of Information Guide Gaze Dynamics in Decision Making

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Experimental research in decision making often relies on tasks that provide participants with all the information they need to make their decisions. Here, we consider the process by which decision makers *seek* information about their choice alternatives when it is not immediately provided. Recent advances in computational theories have proposed that people will seek to process more information about options for which they are less certain about the value. Specifically, they will allocate more attention to options with lower certainty in order to increase their certainty by processing additional information. We tested this hypothesis with a behavioral and eye-tracking experiment in which participants observed pairs of random streams of numerical stimuli and were incentivized to report which streams were generated by the distributions with the greater means. We induced uncertainty by manipulating the variance of the value distribution for each option. In addition, we randomly replaced some of the stimuli with meaningless letters. This decreased the *accessibility* of information about the options. The results show that people fixate more on options with lower accessibility and to a lesser extent options with greater value. Interestingly, this pattern changes across response time, with early fixations driven by variability and accessibility, and late fixations driven by value and accessibility. Moreover, people were more likely to choose options with greater accessibility, and they felt more confident about their choices when accessibility was greater. This research could help illuminate the process of information seeking to reduce uncertainty during choice deliberation.

Keywords: information seeking, process tracing, visual fixations

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continued

There is a vast literature showing that people carry out decisions via a process of integration to boundary. In binary, evidence-based decisions (such as perceptual, medical, or legal decisions), the integrated variable corresponds to the likelihood ratio of the two hypotheses (given a sample of information).[1] In preference-based decisions, the integrated variable corresponds to a difference in the value estimates associated with each alternative. As both likelihood ratios (given a sample of evidence) and value representations are noisy (Gold & Shadlen, 2001; Tajima et al., 2016), the decision mechanism needs to integrate multiple samples across time to enhance the signal-to-noise ratio. Integration to boundary is the most efficient algorithm for executing simple decisions, achieving the fastest response time (RT) for a given accuracy level (Wald, 1945), and is also supported by neural data (Gold & Shadlen, 2001). This decision mechanism accounts well for behavioral data, including the speed–accuracy trade-off (Bogacz et al., 2010; Schouten & Bekker, 1967; Wickelgren, 1977) and the shape of choice-RT distributions, and it has been formalized as the *drift–diffusion model* (DDM; Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008). The DDM is equivalent to normative Bayesian models for simple decisions (Bitzer et al., 2014; Gold & Shadlen, 2001).

While there is much behavioral and neural data in both humans and animals supporting the notion of information accumulation as a mechanism for generating choices, less is known regarding the process of information acquisition itself. For example, when choosing among multiple options (of anything from snacks to stocks), the decision maker often needs to gather information about the individual options—separately and sequentially—by focusing attention (often proxied by visual gaze in behavioral experimental data; Armel et al., 2008) on one option or the other. In turn, attention appears to modulate the choice mechanism as formalized in an extension to the DDM known as the *attentional DDM* (Krajbich et al., 2010). The *attentional DDM* accounts for an important pattern often observed in choice data: People are more likely to choose the option that they looked at longer, even after controlling for other variables such as the relative option values (Armel et al., 2008; Cavanagh et al., 2014; Eum et al., 2023; Fiedler & Glöckner, 2012; Glickman et al., 2019; Krajbich et al., 2010; Shimojo et al., 2003; Smith & Krajbich, 2018, 2019; Stewart et al., 2016).

The main question we wish to examine here is what guides the decision apparatus as it seeks information relevant for making choices between pairs of options. Under the *attentional DDM*, the gaze trajectory is considered to be exogenous to the decision process (Krajbich et al., 2010). Recently, the gaze trajectory was proposed to be guided by the developing preference (e.g., as the accumulation process begins to show a preference favoring one option, attention is more drawn to that option, causing more information to be sampled from it; Gluth et al., 2018). Also, attention has been proposed to be attracted toward individual samples with large numerical values (Tsetsos et al., 2012) or toward samples of information that match the decision goal (Glickman et al., 2018; Sepulveda et al., 2020). Moreover, previous studies have reported that extreme values tend to be more memorable and to impact decisions to a greater degree (Ludvig et al., 2018). Another variable that is likely to modulate the search for information is the uncertainty associated with the choice alternatives. In decisions from experience, people seek more information about options that present higher variability in the possible outcomes (Lejarraga et al., 2012). The strategy of seeking more information for less certain options would be normative under the probabilistic approach to reasoning, where decision-making behavior is driven by an understanding that the world is in-

[1] This can be extended to choices between more options ($n > 2$), but we will focus on the simple ($n = 2$) case here.

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herently uncertain (Friston et al., 2015; Oaksford & Chater, 2001). The literature on curiosity has shown that people seek information that reduces their uncertainty about the world in addition to information that has a positive valence, although that literature investigates information seeking that is noninstrumental to the current decision (see, van Lieshout et al., 2020, for a review).

Some recent theoretical studies have proposed that decision makers should aspire to tune their information processing to maximize decision efficiency. For example, sampling more information about an option for which one is already quite certain of its value would not yield much benefit, as the *value of information* would be low (Howard, 1966). It would be much more useful to instead sample information about an option for which the value estimate is less precise (or more uncertain). This may be a dynamic process. As one observes more samples for an uncertain option, one becomes more certain about it; at some point, the relative certainty about the options might change direction, and it would then become more useful to start observing samples for a different option. This idea has been formalized in recent computational modeling studies (Callaway et al., 2021; Jang et al., 2021; Song et al., 2019) and is supported by evidence showing that people can assess their feelings of value certainty about different options (De Martino et al., 2013; Gwinn & Krajbich, 2020; D. Lee & Coricelli, 2020; D. Lee & Daunizeau, 2020, 2021; D. G. Lee & Hare, 2023; Polanía et al., 2019) and should therefore be able to adjust their behavior as a function of certainty. There is also some preliminary evidence that people indeed look more at options with greater uncertainty (Cassey et al., 2013), but there is still more work to be done in terms of directly demonstrating the links between value, certainty, and attention. Providing evidence in that direction is a central aim of this study. To that end, we designed an experimental paradigm that allows us to control (not only to measure) the temporal uncertainty of choice options as people make decisions based on noisy fluctuating evidence, while we continuously monitor their gaze trajectories.

Uncertainty makes decisions more difficult, but it is often reducible, in principle, by considering more information. As a real-world example, consider a decision between stocks of different companies that you are considering investing in. In this example, your initial uncertainty about the average performance of a stock (e.g., based on your observation of its performance on a single day) could be reduced by observing its performance over longer periods of time—you will become more certain about the average daily return it generates when you observe its performance on more days (Bhui & Jiao, 2023). Recent work has shown that people do incorporate this concept of reduceable (or epistemic) uncertainty in their value estimations, and that they are aware of how it can impede their accuracy (Olschewski & Scheibehenne, 2024). In this study, we examine a classical source of decision uncertainty—value variability—as well as an additional source related to a new variable that we introduce—information *accessibility*. We use the term *accessibility* to refer to the availability of information to be processed about choice options, as well as the ease with which the information can be processed. This could relate to stimulus characteristics such as contrast or clarity for perceptual choices, or to the frequency or recency of previous experiences with an option for memory-based choices. From this perspective, accessibility (or the lack thereof) should affect uncertainty—when a portion of the observed samples of evidence are noninformative, a decision maker will be less certain about the true average value than if all samples were informative. Variability should similarly affect uncertainty—the more stochasticity in the observed samples, the less certain a decision maker will be about the true average value.

With respect to the process by which decision makers select what to sample while deciding, we think both sources of uncertainty outlined above might be significant factors. In brief, the reduction of uncertainty that is purported to take place when attending to an option during a decision should occur at a higher rate both when the observed samples are less variable and when accessibility to meaningful samples is higher. Below, we first describe our experimental paradigm and then outline our general predictions with respect to variability and accessibility.

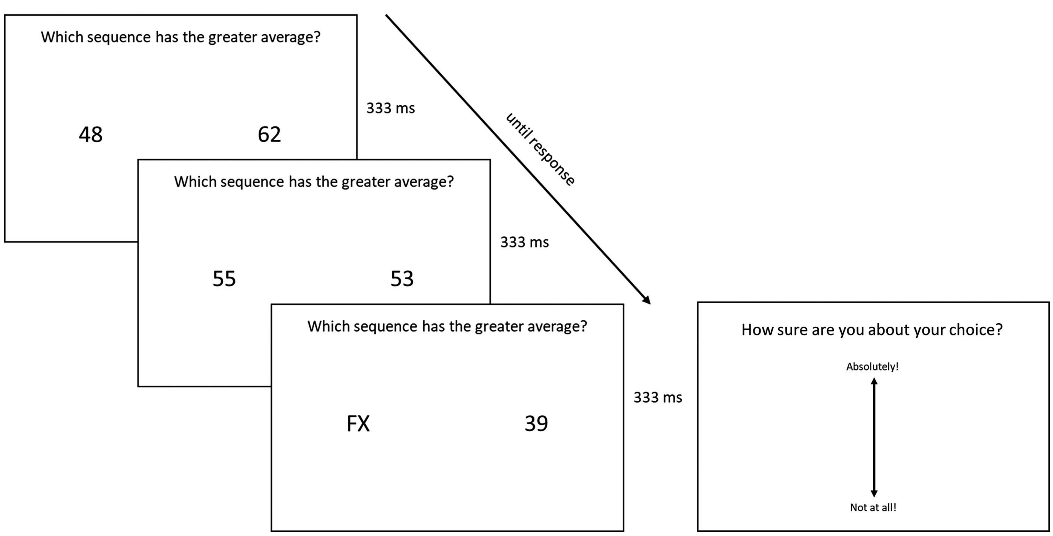
Our experimental paradigm displays pairs of sequences of numerical values (on the left and right sides of the computer screen). This could correspond to returns of pairs of stocks, for example. The numbers are samples drawn from two overlapping Gaussian distributions, which change from trial-to-trial but are fixed within each trial. Sometimes a numerical sample is replaced by a meaningless pair of letters, which decreases the accessibility of the decision-relevant information for the associated option. The samples for both options are simultaneously updated at a rate of three times per second, and they continue to update until participants report their decision (about which sequence corresponds to the generating distribution with the greater mean; see Figure 1 for an illustration). Using this paradigm, we can orthogonally manipulate the option properties (mean, variability, and accessibility) on each trial. The participants maintained control over where they focused their gaze at any point in time while figuring out which option to choose (the direction of which we monitored and recorded) as well as the time at which they terminated each decision. Importantly, the small font size of the displayed samples along with the speed with which they were updated ensured that participants would need to fixate on them in order to properly perceive them. With this design, we were able to make a number of specific predictions (see below) and validate them with the experimental data.

Predictions

Gaze Fixations

We predict that people will spend more time (on average within each trial) looking at the option with higher mean, higher variability, and lower accessibility. In general, people tend to look more at an option when they think it is the best response to the task at hand (Armel et al., 2008; Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Krajbich et al., 2010; Shimojo et al., 2003). Previous theoretical work has also proposed that people should look more at uncertain options in order to reduce that uncertainty by focusing their attention (Callaway et al., 2021; Jang et al., 2021; Song et al., 2019). The more attention an option receives, the more information should be processed about that option. With more information, the initial uncertainty should be reduced to a greater extent than if the option had low uncertainty to begin with (Cassey et al., 2013). There is also initial evidence that people look less at options that are highly accessible (Gwinn & Krajbich, 2020; in that study, accessibility was operationalized in a very different way than in our experiment—participants were asked whether or not they would be willing to consume individual snack foods, and the RT with which they responded was taken as a measure of accessibility for the option; RT was first regressed on rating extremity, and the residuals served as the measure of accessibility). People should pay more attention to poorly accessible options simply because when samples contain less information, more samples will need to be accumulated to achieve the same amount of uncertainty reduction. This should impact where people allocate their attention, as it might behoove them to look more at

Figure 1
An Illustrative Example of a Choice Trial



options with low accessibility in order to extract sufficient information about them.

Choices

Our first set of behavioral predictions relates to value mean. We predict that choice accuracy will be higher, RT will be lower, and confidence will be higher when the mean difference between the options (often termed *choice ease*) is greater. This prediction is a critical one, as it will simultaneously serve to demonstrate whether participants performed the task properly and whether our main difficulty manipulation was successful. We also predict that RT will be lower and confidence will be higher when the mean sum of the options is greater. Previous studies have shown that people decide more quickly and with higher confidence when the total overall value across choice options is higher (Frömer et al., 2019; Hunt et al., 2012; D. G. Lee & Hare, 2023; Polanía et al., 2014; Smith & Krajbich, 2019). It has sometimes also been observed that choices are more accurate when the value sum is greater (Shevlin et al., 2022), but we withhold from making a prediction about this until more corroborating evidence is available.

Our second set of behavioral predictions relates to value variability. We predict that accuracy will be lower, RT will be higher, and confidence will be lower when either the sum of variability across options or the variability of the higher valued option is greater. Feelings of uncertainty that people have about the value of choice options under consideration have previously been shown to influence choices. Specifically, decisions seem to be facilitated (i.e., they are more accurate, faster, and more confident) when there is less uncertainty about the set of options (Gwinn & Krajbich, 2020; D. Lee & Coricelli, 2020; D. Lee & Daunizeau, 2020, 2021; D. G. Lee & Hare, 2023). Similar results were found when the higher valued option was less uncertain relative to the lower valued option (D. Lee & Coricelli, 2020; D. G. Lee & Hare, 2023). We anticipate similar effects in our data.

Our third set of behavioral predictions relates to the key new variable that we examine in this study: information accessibility. We predict that accuracy will be higher, RT will be lower, and confidence will be higher when either the sum of accessibility across options or the accessibility of the higher valued option is greater. We expected accessibility to impact choice behavior in a way similar to variability. The idea is that when information signals are less accessible (here operationalized as a greater probability of meaningless letters being displayed within the streams of numbers), a decision maker will be less certain about the value of the corresponding option. Note that with our experimental design, lower accessibility would necessarily result in longer RT *if* participants were to adopt a strategy of seeking comparable amounts of information about all options before deciding. A prediction of longer RT for trials with lower overall accessibility, therefore, is tantamount to predicting that participants will indeed adopt such a strategy. Our predictions for how accessibility should relate to the various decision variables align with the results from previous studies showing that choices between options that are more easily accessible in memory result in faster response times (Fazio et al., 1992), that options that are more accessible in memory are more likely to be chosen (Gwinn & Krajbich, 2020), and that options that feel more familiar are both more likely to be chosen and chosen more quickly and confidently (D. G. Lee, 2024). They also conceptually align with previous evidence showing that, in general, people prefer options that are easier to process (Oppenheimer, 2008) or that processing fluency magnifies the informational content of the stimuli (Hertwig et al., 2008; Landwehr & Eckmann, 2020). Such factors might be analogous to one option having greater accessibility, hence our anticipation of the potential impact of accessibility difference.

Method

To test the theoretical predictions, we designed an experiment in which we orthogonally manipulate mean, variability, and accessibility. We record gaze fixation patterns with an eye-tracking setup. Our core analyses are based on mixed effects regression models.

Participants

A total of 50 people participated in the experiment (28 female; age: $M = 24$ years, $SD = 5$, range 19–45). All participants were recruited via Tel Aviv University Sona Systems, either through the Department of Psychological Sciences or the Behavioral Lab at the Coller School of

Management. All were self-declared fluent English speakers. As compensation for approximately 1 hr of time, each participant received either a payment of 40 shekels (approximately $11) or course credit. Each participant also received up to 20 shekels as a bonus payment calculated according to performance. The experimental procedure was approved by the Ethics Board of the Department of Psychological Sciences at Tel Aviv University. All participants gave written informed consent prior to commencing the experiment.

Materials

The stimuli used in this study were sequential numerical displays. Each option on each trial consisted of a stream of two-digit numbers randomly generated from a Gaussian distribution with a predetermined mean and standard deviation. Randomly interleaved within each stream were pairs of English letters in the place of the numbers. The displays updated three times per second. We independently manipulated three factors for each option on each trial: *mean*, *variability*, and *accessibility*. The mean corresponded to the mean of the Gaussian distribution from which the individually displayed numbers were drawn. The variability corresponded to the standard deviation of the distribution from which the numbers were drawn. The accessibility corresponded to the probability that each display sample would be a number (rather than a pair of letters, which were explained to be task-irrelevant distractors). We created pairs of options using a $2 \times 2 \times 2$ design for *mean difference*, *variability difference*, and *accessibility difference* (low vs. high for each variable). Specifically, we created each pair as follows. We set the value of one of the options (randomly assigned to the left or right) to a random sample from a uniform (40, 55) distribution. We then set the value of the other option to the value of the first option plus either 4 (low mean difference condition) or 8 (high mean difference condition). We set the variability of one of the options (randomly assigned to the left or right) to 6 and the variability of the other option to either 8 (low variability difference condition) or 12 (high variability difference condition). We set the accessibility of one of the options (randomly assigned to the left or right) to 90 and the accessibility of the other option to either 80 (low accessibility difference condition) or 70 (high accessibility difference condition). Crucially, we manipulated these three factors independently so that they were orthogonal to each other, meaning that knowing something about the accessibility of one option does not provide any information about the mean or variability of the other option on any trial. Once all the choice pairs had been created, we shuffled them such that trials from the eight conditions would appear in a random order across the experiment.

Procedure

Participants were asked to report which stream of numbers (the left or right option) they believed came from the distribution with the greater mean. They were instructed to consider the true generating means of the random processes, not the exact means of the specific samples they observed. They were instructed to ignore the letters that sometimes appeared instead of numbers, as there was no significance to them and they served only as distractors. All participants confirmed that they understood the instructions and were able to successfully explain the task back to the experimenter. Participants were informed that the experiment would consist of 200 trials, without any time limits. They were informed that all trials were independent—they should respond only according to the current trial without considering the previous trials. After every 40 trials, participants were given the opportunity to take a self-paced break before continuing.

On each trial, a pair of options was presented on the computer monitor (one on the left side of the screen at 25% of the width of the screen starting from the left, one on the right side at 75% of the width of the screen starting from the left; see Figure 1). Importantly, the distance from the center, the fairly small font size (50 point), and the rapid rate of change rendered it impossible for participants to see what was displayed on a given side of the screen unless they diverted their gaze toward that side. This was confirmed by debriefing during pilot testing. At the top of the screen, the question "Which sequence has the greater average?" was displayed. Trials were self-paced; the displays continued to update until participants entered a response. Participants used the left and right arrows on the computer keyboard to enter their choice of the left or right option, respectively. After reporting their choice on each trial, the options disappeared, and a vertical slider scale for choice confidence appeared at the center of the screen. Participants were asked, "How sure are you about your choice?" They used the up and down arrow keys to move a cursor along the scale anywhere from "Not at all!" (minimum confidence) to "Absolutely!" (maximum confidence). They submitted their confidence rating by pressing the space bar. After reporting the confidence on each trial, the scale disappeared, and participants received feedback about their performance on that trial. Specifically, if they answered correctly on that trial, a green "+1" appeared at the center of the screen; if they answered incorrectly, a red "−1" appeared. Thus, on each trial, participants either gained or lost 1 point. At the end of the experiment, we converted the cumulative point total to a monetary bonus payment at the rate of 10 points = 1 shekel. A participant who responded correctly on all trials would therefore earn a bonus of 20 shekels; a participant who responded randomly (or otherwise performed at or below chance level) would not earn any bonus. (No participants earned negative points, but if they had, the amount of their bonus would have been zero, not a reduction of their base payment).

Eye Tracking

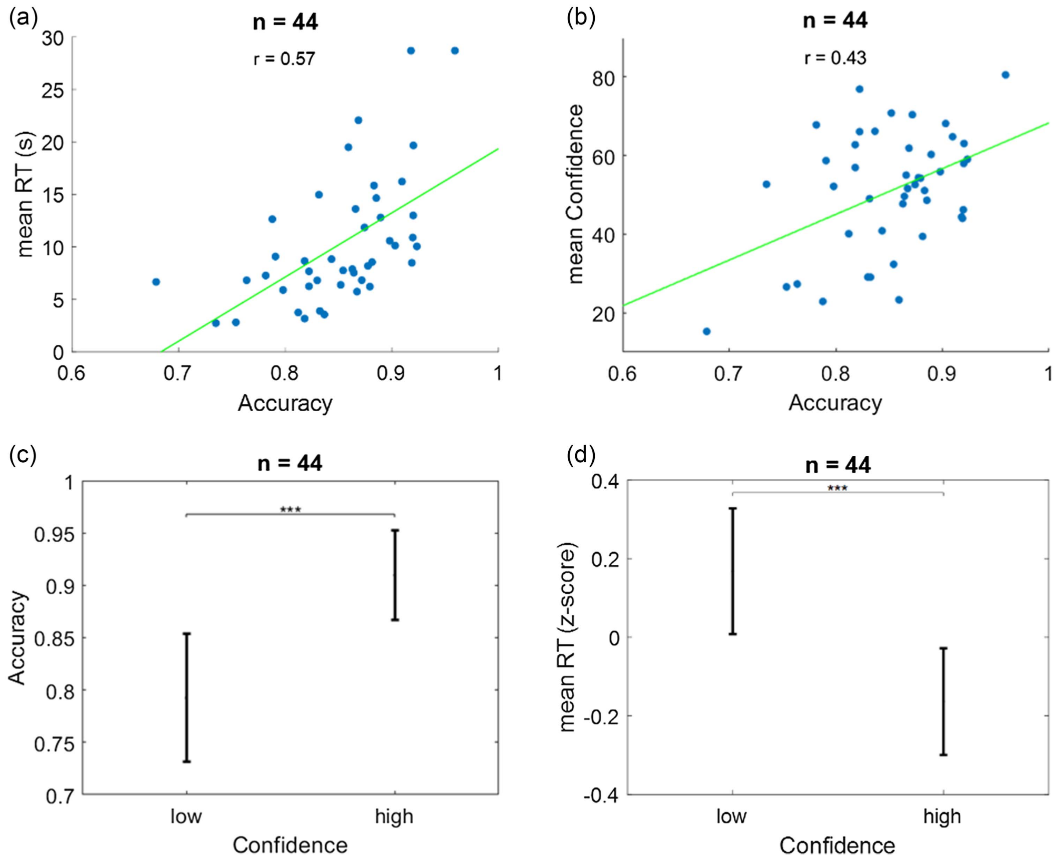
We recorded eye gaze fixation location (with a particular interest in the *x*-coordinates) continuously throughout the experiment using a Tobii-Pro eye tracker. We set the sampling rate to 120 Hz. Each participant performed the default calibration task prior to commencing the experiment. After collecting the data, we divided it into epochs for each trial (for each participant) using the "trial onset" and "response" triggers that we included in our data collection script. We averaged the *x*-coordinates for the left and right eyes and used that as our measure for the gaze location. For any points in time where the eye tracker failed to record a signal (e.g., during blinks), we interpolated from the surrounding signals. Specifically, for any contiguous gaps, we set the values within those gaps equal to the average of the immediately preceding and subsequent values. Finally, we classified gaze direction as being toward the left at any point in time if the *x*-coordinate was somewhere less than 40% of the width of the screen and as being toward the right if the *x*-coordinate was somewhere greater than 60% of the width of the screen. Whenever the *x*-coordinate was somewhere between 40% and 60% of the width of the screen, we classified gaze direction as being toward the center. In all relevant analyses reported below, we ignored gazes toward the center and only considered gazes toward the left and right (i.e., toward the choice options).

Results

Before undertaking our main analyses, we first checked to see if any participants failed to meet our performance threshold of 60% accuracy. We determined this threshold by calculating the standard error of a binomial distribution of random choice ($p = .5$) and adding three times the standard error to chance level. Two participants performed worse than this threshold, so we excluded those participants from our analyses. We also excluded four additional participants because their eye-tracking data did not record properly. All analyses reported below are therefore based on the remaining 44 participants. We note that the behavioral results did not change when we repeated the analyses without excluding the four participants with missing eye-tracking data, but we decided to exclude them nonetheless for consistency with reporting the gaze-related results. For each participant, we excluded from analysis all trials with outlier RTs—defined as within-participant median log(RT) ±three times the within-participant median average deviation of log(RT). For the model-free analyses reported below, all significance levels were determined by two-sample *t* tests. For the regression analyses, we used the *fitlme* function in MATLAB. All regression analyses were based on mixed effects models with participants as random effects (both intercepts and slopes). In each of our regression models, we replace all predictor variables with their *z*-score transformations and keep the outcome variables in their original form. By doing so, the resultant regression coefficients are semipartial correlations between the independent and dependent variables and can thus provide an objective indication of effect sizes that is easy to interpret.

As a preliminary check for the general quality of our data, we performed a series of cross-participant tests. First, we observed a clear *speed–accuracy trade-off* across participants—those who achieved higher accuracy had longer average RT ($r = 0.57$; Figure 2a). Second, we observed *metacognitive calibration* (subjective confidence aligned well with objective accuracy) across participants—those whose accuracy was higher had higher average confidence levels ($r = 0.43$;

Figure 2
Cross-Participant Relationships Between Accuracy, Response Time, and Confidence



Note. Dots represent individual participant averages. Error bars represent means ±standard errors. RT = response time. See the online article for the color version of this figure.
*** $p < .001$.

Figure 2b). Third, we observed *metacognitive sensitivity*. Specifically, when separating trials according to a median split on confidence (within-participant), high confidence trials corresponded to accuracy levels significantly greater than those for low confidence trials (mean difference = 0.117, $p <$ .001; Figure 2c). Fourth, we observed a negative relationship between confidence and RT—when separating trials according to a median split on confidence (within-participant), low confidence trials corresponded to significantly greater RT than did high confidence trials (RT z-scored within-participant; mean difference = 0.332, $p < .001$; Figure 2d).

For the remaining analyses, we computed what we call the *observed input* variables to use instead of what we call the *generative input* variables. The generative (i.e., hypothetical or steady-state) input simply refers to the trial-by-trial parameters that we established in our experimental design: the mean and standard deviation of each Gaussian random number generator and the probability that each display update would contain a number rather than a letter. The observed input refers to parameters that summarize what the participants actually saw on each trial. Because we designed the experiment such that participants would not likely be able to see the stimulus on the right side of the screen while their gaze was focused toward the left (and *vice versa*), we decided that it made the most sense for us to include as input data only the information from stimuli that the participants explicitly gazed at. We were able to do this because on each trial, we recorded the exact streams of numbers and letters that were displayed as well as the exact timing of when participants were looking at the left or right options. We thus know exactly which sets of numbers and letters participants observed for each option on each trial. Our observed input for each option is the mean and standard deviation of these observed sets of numbers, and the percentage of numbers contained within each set.[2] From this point forward, when we refer to the mean, variability, and accessibility variables, we refer to these observed input variables.

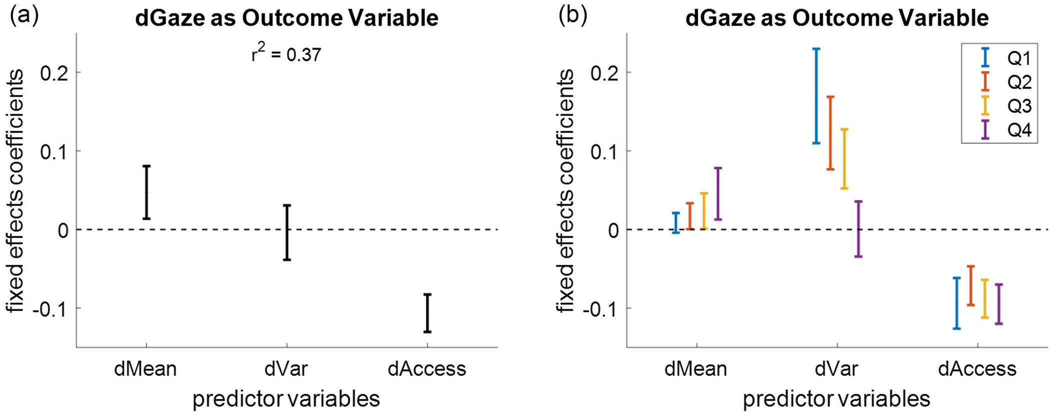
Dependency of Gaze on Decision Variables

We wanted to test how the decision variables (mean, variability, and accessibility) might affect gaze allocation across the full duration of each trial. We thus first calculated the percentage of time within each trial that the gaze was to the left or to the right (or neither). We calculated the percentage of time within a trial that the gaze was to the left minus the percentage to the right (ignoring gazes toward the center) and labeled this variable as gaze percentage difference (dGaze). We then regressed dGaze on differences in each of the decision variables, mean difference (dMean), variability difference (dVar), and accessibility difference (dAccess); all left minus right. All variables were z-scored across trials and participants before entering the regression design matrix. We found that participants gazed more at the option (within a choice pair) with the higher mean (regression coefficient = 0.05, $p = .006$) and less at the option with higher accessibility (regression coefficient = −0.11, $p < .001$), in line with our predictions. However, we did not find our predicted effect of variability on gaze allocation ($p = .821$). Together, our regressors accounted for 37% of the variance in gaze percentage difference (see Figure 3a).

We thought it might be possible that the drivers of gaze allocation were dynamic in the sense that they might develop across decision time. Specifically, the impact of each decision variable on gaze might differ from the beginning to the end of each trial. The idea is that people would look more at uncertain options at the beginning of the trial in order to gather more information and increase their certainty about the mean estimates, whereas toward the end of the trial, people might instead look more at the options for which their mean estimates were highest. To test this, we divided the data into quarters based on time from stimulus onset until eventual response (within each trial for each participant). We regressed dGaze during the first quarter of each trial on the same regressors as before (dMean, dVar, dAccess) except now calculated using only the samples that the participants observed during the first quarter of each trial. We then regressed dGaze during the second, third, and fourth quarters of each trial (Q1–4) on dMean, dVar, and dAccess, now calculated according to all samples that participants observed through that time interval (i.e., Q2 included samples from Q1 to 2, Q3 included samples from Q1 to 3, Q4 included samples from Q1 to 4). This is because during each quarter of a trial, participants would retain the information that they had acquired during the previous quarters of that trial. The values of dGaze for each quarter were calculated in a similar manner. All variables were z-scored across trials and participants before entering the regression design matrix. We found that at the beginning of trials, participants did indeed gaze more at more uncertain options (regression coefficient = 0.17, $p < .001$). They also gazed less at more accessible options (regression coefficient = −0.09, $p < .001$). We did not find a significant effect of mean on early gaze fixations ($p = .189$). The pattern was different at the end of trials. Now, mean did have a significant impact on gaze allocation, with participants looking more at the higher valued option (regression coefficient = 0.05, $p = .007$) as well as the lower accessibility option (regression coefficient = −0.10, $p < .001$). We did not find a significant effect of variability on where participants looked toward the end of each trial ($p = .974$). This differentiation between early and late effects seems to have arisen across time, as demonstrated by the gradual change in regression coefficients from Q1 to 4 (see Figure 3b). The gradual increase in weight for mean was only a trend, but the decrease in weight for variability was statistically robust for every time bin (see Supplemental Material).

[2] We also considered an alternative approach, in which the input variables were "accumulated." Specifically, within each gaze fixation, we weighted the contribution of each sample according to the amount of time that it was observed. This basically meant that samples at the beginning and end of each fixation were given less weight than the other samples. The results of all analyses reported below were qualitatively identical and quantitatively similar when using these accumulated input variables.

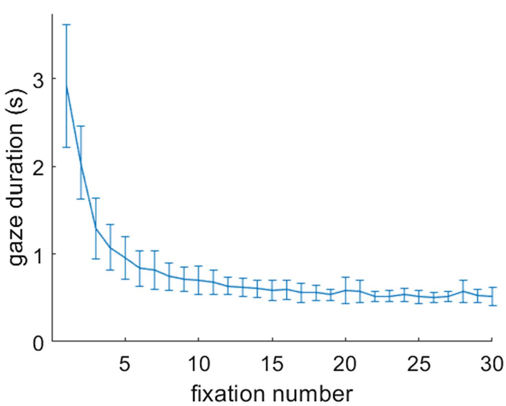
Figure 3
Regression Coefficients for Gaze Percentage Difference



Note. Shown here are the fixed effects coefficient estimates when regressing gaze percentage difference (left minus right) on differences (all left minus right) in mean difference (dMean), variability difference (dVar), and accessibility difference (dAccess). (a) shows the effects at the full-trial level. (b) shows the effects for the first, second, third, and fourth quarters of each trial (Q1–4; see legend for color code). The regressors within each time interval are based on an accumulation of observed samples since trial onset. Error bars represent 95% CI. CI = confidence interval; Q = quarter; dGaze = gaze percentage difference. See the online article for the color version of this figure.

Finally, we tested whether the duration of fixations changed across time (within trials). We found that the duration gradually decreased, with early fixations lasting longer and later fixations reaching an apparent lower asymptote (see Figure 4). This could possibly be explained by assuming that early fixations need to endure longer to enable the decision maker to establish the "context" (e.g., which option has greater variability or information accessibility) for the current decision.

Figure 4
Fixation Duration Across Time



Note. Early fixations (within each trial) had longer gaze duration than later fixations. See the online article for the color version of this figure.

Are the Observed Gaze Patterns Normative?

From a normative perspective, as participants refine the precision of their mean estimates, they should sample more when the samples they observe are either less accessible or more variable. We tested for such normative behavior by examining the streams of samples that participants observed. First, we counted the observed meaningful samples (i.e., numbers rather than letters) for each option on each trial for each participant. We then calculated the mean of the count of meaningful samples for each participant (across trials and options), separately for low and high accessibility options (median split within-participant). We found that there was no significant difference between the low and high accessibility options (low = 13.22, high = 13.87, difference p = .154). This suggests that participants used a similar sampling strategy for options with low or high accessibility, after accounting for the meaningless samples. We then tested for correlations between accessibility and number of meaningful samples (within-participant). Across participants, we found a significant average correlation (0.05, $p = .018$). This qualitatively differs from the average correlation between accessibility and number of *total* samples (−0.06, $p < .001$). This demonstrates that participants appropriately observed more total samples for options with lower accessibility, but that they might not have fully compensated for lower accessibility by observing enough additional samples (possibly due to an increasing cost of sampling or an urgency signal encouraging a response).

We repeated the above analyses with respect to variance instead of accessibility. We did not find a significant difference between the low and high variability options (low = 13.36, high = 13.39, difference $p = .823$). This suggests that participants used a similar sampling strategy for options with low or high variability, after accounting for the meaningless samples. We then tested for correlations between variability and number of meaningful samples (within-participant). Across participants, we did not find a significant average correlation (0.02, $p = .105$).

The theoretical benefit of observing more samples when estimating the mean of a distribution would be to reduce the standard error of the mean estimate (SEM). We thus tested whether participants seemed to sample in a manner that might best achieve this goal. For each option for each trial for each participant, we traced the evolution of the SEM across the observed samples. Then, for each trial, we recorded both the final SEM of each option at the time of the response and the maximum SEM for each option over the course of the trial. We then divided individual options based on accessibility (median split within-participant) and pooled the options across participants. We found that there was no difference in either the max SEM (low mean = 5.68, high mean = 5.64, difference $p = .362$) or the last SEM (low mean = 2.59, high mean = 2.52, difference $p = .069$) between low and high accessibility trials. We performed a similar test based on low versus high variability options and found a significant difference in max SEM (as expected; low mean = 5.17, high mean = 6.12, difference $p < .001$) as well as in last SEM (low mean = 2.36, high mean = 2.75, difference $p < .001$). The difference in last SEM, however, was much smaller than the difference in max SEM (−0.39 vs. −0.95, $p < .001$). Together, this suggests that participants considered the accessibility and to a lesser extent the variability of observed samples when determining how long to continue sampling, perhaps with the notion of achieving a target level of SEM for each option before deciding.

Relationships Between Decision Variables and Choice Behavior

We then examined choice behavior (accuracy, RT, and confidence) to test our predictions. We tested for effects of all our independent decision variables—mean sum, dMean, variability sum, dVar, accessibility sum, and dAccess—on each of our dependent variables separately. Recall that all independent variables were calculated based only on the samples (numbers and letters) that the participants actually observed for each option on each trial. All the difference terms were calculated based on the higher mean-valued option minus the lower mean-valued option. In this way, the correlations that would have otherwise existed between variability sum and dVar and between accessibility sum and dAccess are nullified (see Supplemental Material). Accuracy is based on the greater true generative mean for each trial, which is what participants knew they had to report. To test for potential effects when examining all independent variables simultaneously, we conducted a series of mixed effects regression analyses. The fixed effects regressors in each model were the independent variables listed above. All variables were z-scored across trials and participants before entering the regression design matrix. The models included a logistic regression of accuracy and linear regressions of log(RT) and confidence.

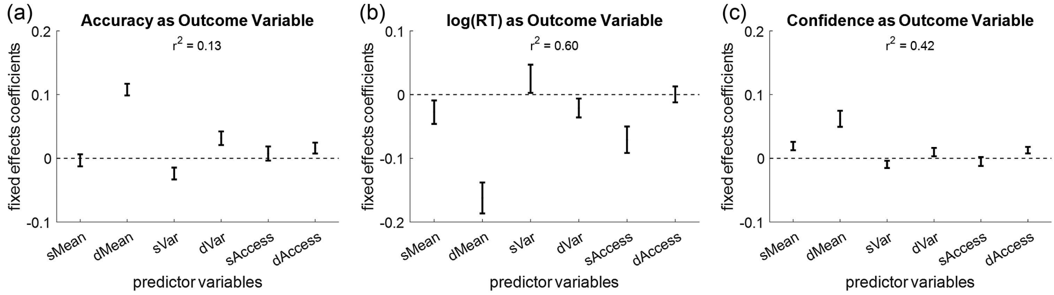
As expected, there was a strong effect of mean difference on all three behavioral variables (regression coefficients: accuracy: = 0.11, $p < .001$; RT = −0.16, $p < .001$; confidence = 0.06, $p < .001$). Consistent with previous findings, there was a significant effect of mean sum on RT (regression coefficient = −0.03, $p = .003$) and confidence (regression coefficient = 0.02, $p < .001$), but not on accuracy ($p = .515$). Consistent with previous findings, there was an effect of variability sum on all three behavioral variables (regression coefficients: accuracy = −0.02, $p < .001$; RT = 0.02, $p = .029$; confidence = −0.01, $p = .001$). There was a significant effect of variability difference on all three behavioral variables, but the pattern of results was the opposite of what has previously been reported (regression coefficients: accuracy =

0.03, $p < .001$; RT = −0.02, $p = .005$; confidence = 0.01, $p = .004$). As we predicted, there was a significant effect of accessibility sum on RT (regression coefficient = −0.07, $p < .001$), but we did not find our predicted effect of accessibility sum on accuracy or confidence ($p = .186$ and $p = .153$, respectively). As we predicted, there was a significant effect of accessibility difference on accuracy (regression coefficient = 0.02, $p < .001$) and confidence (regression coefficient = 0.01, $p < .001$), but we did not find our predicted effect of accessibility difference on RT ($p = .961$). Together, our regressors accounted for 13%, 60%, and 42%, respectively, of the variance in accuracy, log(RT), and confidence (see Figure 5).

Next, we examined the eye-tracking data to test for associations between gaze and choice, while accounting for the primary explanatory variables analyzed above. First, we ran a logistic regression of choice (probability of choosing the left option) on the differences (left minus right) of mean, variability, accessibility, and gaze percentage (i.e., the percentage of time within a trial that the gaze fixation was to the left minus the percentage to the right). All fixed effects coefficients were positive and significant (mean difference = 1.90, variability difference = 0.23, accessibility difference = 0.09, gaze difference = 0.14; all p-values < .001; Figure 6a). In particular, this was true for the coefficient reflecting the relationship between gaze and choice (beyond the effects of mean, variability, and accessibility), which replicates previous findings (Gwinn & Krajbich, 2020). Interestingly, but in line with the results reported above, the coefficient for variability difference shows that people were more likely to choose the option associated with *greater* variability, which is counter to previous findings as well as our prediction. We also note that the intercept term was positive and significant (0.50, $p < .001$), indicating that participants tended to prefer the option on the left. Together, our regressors accounted for 58% of the variance in choice probability.

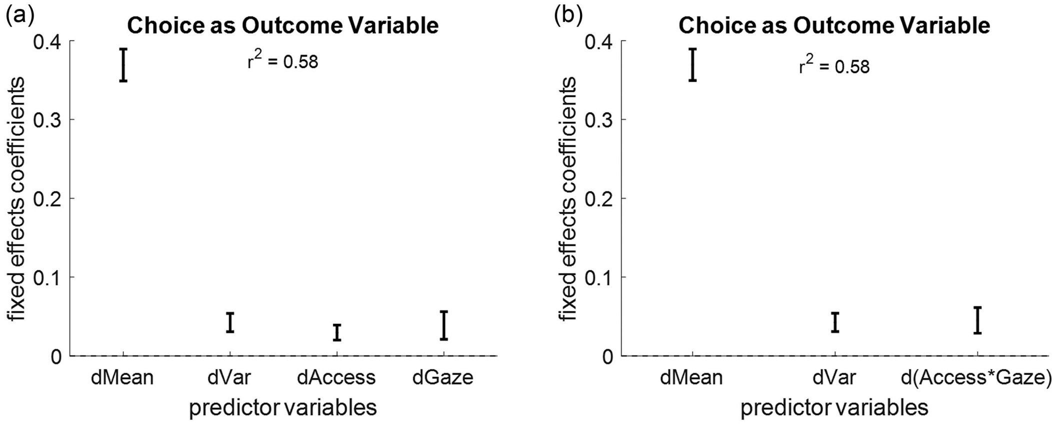
Gaze time and accessibility rate both represent different aspects of a similar phenomenon: accumulating information. The number of total samples observed is determined by gaze time, and the percentage of those samples that are informative is determined by accessibility rate. Together, this means that the combination of the two (Gaze × Accessibility) represents the number of informative samples observed for an option. To validate our hypothesis that gaze and accessibility were two parts of a unified variable, we repeated the regression of choice this time replacing dAccess and dGaze with d(Acc × Gaze). The results were very similar, regression coefficient for d(Acc × Gaze) = 0.16, $p < .001$; Figure 6b. Note that the simplified model performs at a level identical to that of the more complex model (both $r^2 = 0.58$), suggesting that information sampling rate is the critical element whether controlled by the experimenter (via accessibility) or the participant (via gaze fixation). We repeated the regression again this time replacing dAccess and dGaze with the difference (left minus right) in the total count of numerical samples observed for each option within a trial (which we label dN for difference in numerical samples). Again, the results were very

Figure 5
Regression Coefficients for Choice Behavior



Note. This figure shows the fixed effects coefficient estimates when regressing accuracy (a), log(RT) (b), and confidence (c) on mean sum (sMean), mean difference (dMean), variability sum (sVar), variability difference (dVar), accessibility sum (sAccess), and accessibility difference (dAccess). Error bars represent 95% CI. RT = response time; CI = confidence interval.

Figure 6
Regression Coefficients for Choice Probability



Note. (a) Fixed effects coefficient estimates when regressing choice (probability of choosing the left option) on differences (all left minus right) in mean difference (dMean), variability difference (dVar), accessibility difference (dAccess), and gaze percentage difference (dGaze). (b) Fixed effects coefficient estimates when regressing choice on dMean, dVar, and the difference in the product of accessibility and gaze percentage (d(Access × Gaze)). Error bars represent 95% CI. RT = response time; CI = confidence interval; d = difference.

similar (regression coefficient for dN = 0.41, $p <$ .001; $r^2 = 0.57$).

A correlation matrix of the main decision variables, a summary of the correlations between generative parameters and observed parameters, and a histogram of gaze fixation locations are provided in the Supplemental Material.

Discussion

In this study, we examined the drivers of gaze fixation patterns across decision time in a two-alternative forced choice paradigm. Specifically, we sought to validate recent theoretical claims that fixations should be directed more toward choice options whose values are more uncertain. Attention to a specific option is thought to trigger additional information processing about that option, which in turn should help reduce the uncertainty about its value. Fixations should thus be directed toward options with higher variability in noisy evidence about their true value. For similar reasons, fixations should be directed toward options with lower information accessibility. The beneficial information processing that attention can enable will be reduced when the accessibility of information about an option is lower, meaning that people would have to maintain their gaze fixation longer on that option in order to extract information about it. Our data only partially validated these hypotheses. At the full-trial level, relative gaze dwell time favored options whose observed stimulus samples were less accessible (i.e., more of the samples were meaningless letters), but not those whose samples were more variable (i.e., the standard deviation of the observed numerical values was greater).

The former is consistent with the idea that the purpose of a gaze fixation is to allocate attention to an option with the intention of extracting information about it. Nonnumeric samples directly reduce the information content in a given stream. Once people shift their gaze toward an option, the informativeness of the samples that they obtain might determine how long they linger before shifting their attention toward the other option. It thus seems that people might behave at least somewhat normatively when deciding how long to fixate on each option, at least with respect to information accessibility. It could be that the goal is to extract a specific amount of information about each option and to respond when a predefined certainty criterion has been achieved for one estimate being greater than the other. Our findings related to the final standard errors of the mean estimates on each trial—irrespective of accessibility—support this idea. Future studies are needed to identify the putative normative criterion to terminate a fixation, which should depend on participant-specific parameters for how costly accumulating evidence is and how beneficial increased certainty is (Fudenberg et al., 2018; D. G. Lee & Daunizeau, 2021; Tajima et al., 2016).

Our participants seemed to pay more attention to highly variable streams of numerical samples at the beginning of each trial. However, as noted above, it seems that they did not pay more attention to highly variable streams of numerical samples across the full duration of a trial. This might make sense if gaze fixations serve to enable information gathering. People may accumulate information across fixations rather than within them, in which case they may simply observe a series of samples for each option before switching their attention back to the other option—hence, at the whole-trial level, they would have no need to look more at the option with greater variability.

With respect to value, people should seek information about both options (at least at the beginning of each trial). The purpose of a fixation might thus be to extract information regardless of its content, because developing a sense of the average value of an option would benefit from obtaining both high- and low-valued samples. However, after multiple fixations to each option, people may start to form a belief about which is more valuable, and they will respond when this belief becomes strong enough. By the end of the trial, people will start to look more at the option that they are preparing to choose. This could explain our finding that our participants fixated more on the option with the higher mean across the full trial—and especially late in the trial.

According to our interpretation of the gaze allocation results discussed above, we expected a different pattern early in the trial that would gradually transform into the full-trial pattern as information accumulated across the trial. Indeed, this is what we found. Specifically, we found that our participants did not pay more attention to more valuable options at the beginning of the trial, but that a bias in attention gradually increased with longer time epochs. We also found that our participants paid more attention to the more variable options at the beginning of the trial, and that this bias in attention gradually disappeared when considering increasing time epochs. With respect to accessibility, we found that our participants paid more attention to options with lower accessibility, both early on and across the whole trial. This is interesting because it distinguishes the detriment to mean estimation caused by variability from that caused by accessibility. When people seek more information by initiating an additional fixation, the presence of distractor samples never provides any information. In that case, people may maintain their fixations longer as they wait for the information that they continue to seek. This explanation for the dynamic pattern of these results also aligns with our finding that early fixations endured longer than later fixations. It could be that at the beginning of each trial, uncertainty is maximal, so more samples are needed when the variability of the samples is high. Later in the trial, samples obtained from additional fixations might simply be accumulated together with earlier samples to fine tune the emerging value representations. In that case, fewer samples (i.e., shorter fixations) would be needed to revise a value representation (later in the trial) than to establish it in the first place (early in the trial). This speculative interpretation of our findings remains to be fully tested in future studies.

Previous studies have reported a “gaze bias” in which people choose options that they viewed for longer, even after controlling for value difference. This has been shown in preferential choice (Gluth et al., 2020; Sepulveda et al., 2020; Smith & Krajbich, 2019), risky choice (Fiedler & Glöckner, 2012; Smith & Krajbich, 2018; Stewart et al., 2016), and even perceptual choice (Tavares et al., 2017). We show that this effect also holds in the domain of numerical averaging. This is intriguing since there was no subjective component to our task—participants simply had to form rough latent estimations of the means of the two numerical streams and report which one was greater. Our finding aligns with the interpretation that attention magnifies information that aligns with any decision goal (Sepulveda et al., 2020).

Although previous studies have interpreted the observed effect of gaze on choice as a bias, this is not the only possible interpretation. It could be that looking longer at an option is tantamount to collecting more information samples about that option, in which case the subjective precision about the value estimate of that option would be greater than for the other option. Since people prefer options for which their subjective precision or certainty is greater (Frömer et al., 2022; D. Lee & Coricelli, 2020), this could be a simple explanation for the “gaze bias.” In our experimental paradigm, gazing longer at an option is synonymous with observing more samples about it, holding constant the accessibility rate. For any option, the relative gaze time multiplied by the relative accessibility rate directly computes the relative number of informative samples about that option. We validated this logic by showing that a regression of choice that included the difference in Accessibility × Gaze provided results indistinguishable from those of a model including the difference in accessibility and the difference in gaze proportion as independent regressors. Furthermore, a model that replaced accessibility and gaze with a direct count of numerical samples (left option minus right option) was also nearly indistinguishable.

With our behavioral results, we demonstrated the importance of information accessibility and its influence on choice: accuracy, RT, and confidence. We found that choices are significantly faster when there is greater overall accessibility across the options. This makes sense, because it means that the same amount of information can be gained sooner as the potential rate of information processing is higher. This increase in speed was not matched with an increase in confidence, as is usually the case. Perhaps this is because people often use the speed with which they could determine their response as an indicator of the likelihood that they were correct, whereas in this case, this correspondence is polluted by the inclusion of distractors. Simply put, people might realize they are slower when accessibility is lower not because the trial is more difficult, but simply because they have to wait longer to ignore the distracting letters. We also found that our participants were more accurate and more confident when the correct option had greater accessibility than the incorrect option. This could be due to the apparent preference that they had for choosing the option with greater accessibility (and thus they would be more accurate when that option was the correct one).

The preference that our participants showed for options with high accessibility—on top of their preference for high mean—is intriguing. Perhaps when accessibility is low in our task, the presence of many distractor letters makes mean estimates less precise, and this lack of precision deters participants. Future work could test this hypothesis by requiring participants to report mean estimates and confidence levels for individual options with different accessibility levels. A tendency to prefer high accessibility options could also be indicative of a leaky accumulation process while people are developing a value estimate from incoming input signals (Usher & McClelland, 2001). The latent mean estimates that participants form during our task could be updated optimally (e.g., in a Bayesian manner) with each new numerical sample that they observe. But, when they observe letters rather than numbers, their value representations might decay toward their (flat) priors. Future work should investigate this issue further, possibly by varying the length of time between stimulus updates and/or the presence of distractors versus empty space.

Our behavioral results replicate many previous findings, including the unsurprising result that high mean difference corresponds to higher accuracy, faster RT, and higher confidence. We also replicated the intuitive result that the sum of variability in information about a pair of options corresponds to lower accuracy, slower RT, and lower confidence (D. Lee & Coricelli, 2020; D. G. Lee & Daunizeau, 2021; D. G. Lee & Hare, 2023). Interestingly, we also replicated the finding that the sum of values across options corresponds to faster RT and higher confidence. This has been show in preferential choice (Frömer et al., 2019; D. G. Lee & Hare, 2023; Smith & Krajbich, 2019), risky choice (Hunt et al., 2012), and even perceptual choice (Polanía et al., 2014). We show that this effect also holds in the domain of numerical estimation. This might suggest that individual samples with large numerical values are inherently salient, causing them to be processed faster because they receive more attentional resources. Or it might simply be that "large" stimuli contain more information, regardless of the form that the information takes. The idea would be that neural activity in response to the query, "How large is this (in whatever relevant dimension)?" would be greater for larger-valued samples and thus allow the response to be formed more quickly.

Perhaps the most unexpected of our behavioral results was the apparent preference that participants had for the option with the greater variability (see Figure 6). Participants were also more accurate, faster, and more confident on trials where the correct option displayed more sample variance than the incorrect option. This is the opposite of what has been reported in preferential choice, where people favor options for which they feel more certain about the values (Frömer et al., 2022; D. Lee & Coricelli, 2020; D. G. Lee & Daunizeau, 2021; D. G. Lee & Hare, 2023). It is also opposite to the very concepts of ambiguity aversion (Ellsberg, 1961) and risk aversion (Pratt, 1964). However, it is in line with the tenets of selective integration theory (Glickman et al., 2018; Tsetsos et al., 2012; Usher et al., 2019). According to that line of work, when participants must choose between a pair of numerical streams (as in our experiment), they are biased in favor of the option whose samples are generated by the distribution with the greater variance. The theory explains this phenomenon by proposing an increase in the relative weighting of the sample draw (left or right) that is greater in numerical magnitude at any point in time. The option with the greater variance will have more numerically high sample draws, which will receive an increased weighting. The same option will also have more numerically low sample draws, but those will effectively be ignored because attention will be directed toward the other option during those time epochs. The net effect is that the comparison of mean estimates ends up being biased in favor of the high-variance option. A key difference between the designs in the selective integration studies and ours relates to the ability to view both streams of numbers simultaneously. In those previous studies, the stimuli displays were positioned close together on the computer screen, intentionally allowing participants to view everything at the same time. In our study, we intentionally positioned the stimuli displays far apart on the computer screen because we aimed to ensure that participants could only observe one option at a time by directing their gaze toward one side of the screen. Therefore, we cannot directly apply the selective integration theory (as it has previously been described) to our current work. However, it is possible that the fundamental principles of the theory nevertheless apply. If numerically larger samples are more salient than numerically smaller samples, this would trigger a larger automatic arousal when larger numbers are displayed. The increase in attention caused by the arousal would in turn give those samples a greater weight as they are combined with other samples to form an estimate of the mean. The end result would be that people would overestimate the means for streams of numbers with high-variance relative to low. If true, this would explain the preference for options with greater variability that we observed in our data. Preliminary (unpublished) evidence from our team supports this—in a task where participants had to estimate the means of solitary streams of numbers, there was an average overestimation and the degree of overestimation positively correlated with the standard deviation of the observed samples (but see, Olschewski et al., 2021, for conflicting evidence). Future work might attempt to better understand this curious result and resolve its origin. Perhaps the explanation is something as simple as: when people see a very high outlier sample for an option, it makes it seem obvious that that is the option with the greater mean; since the task is precisely to find the option with the greatest mean, there might not be a similar effect for very low outlier samples.

Finally, there is an interesting relationship between the concepts of variability and *inaccessibility*. In some ways, the concepts are similar. For example, variability and inaccessibility both reduce the efficiency of information sampling. They both, therefore, likely interfere with the ability of participants to estimate the mean values of the number streams in our experiment. Yet, the concepts are also different in some fundamental respects. For example, variability (in the form of sample distribution variance) makes it more difficult to infer the mean value but inaccessibility should only slow it down (i.e., a display of letters should not impact the latent value representations). However, inaccessibility might also make the task more difficult if the dynamic mean estimation process has a leak or decay. In that case, the precision of the option value representations that develops over time by incorporating additional numerical samples might dissipate when letters are instead observed. This could explain why low accessibility (sum) and high variability (sum) showed very similar effects in the behavioral data (choice, RT, and confidence). This speculative interpretation of our findings remains to be fully tested in future studies that include computational modeling.

Constraints on Generality

The participants in our study were predominantly Israeli students. We have no good reason to believe that the results should differ in participant pools of other origins, but that is an empirical question. Similarly, our participants were predominantly aged in their early 20s, so we cannot be sure if testing older adults would yield similar results. The choice options in the data set we analyzed were all streams of numbers, so we cannot be sure if similar results would arise in other domains. We believe that different elicitation methods for or different operationalizations of the concept of familiarity or information availability should yield similar results, though we acknowledge that that is an empirical question.

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