

Are perceptual decisions influenced by working memory?

Oluwagbemiga Odebode

Abstract:

Visual perception results from the brain interpreting the light that falls on our eyes. But does our perception only depend on what we see, or is it also influenced by what we remember? The purpose of my project is to use psychophysical methods to investigate this question. Twenty-nine subjects were tested using a custom-designed web application. Subjects remembered two “sample” square images, composed of different fractions of red-green pixels. The samples were removed, and the subjects were presented with a third square (“probe”) whose red-green composition was in-between the samples. The subject decided which remembered sample was most similar to the probe. This process was repeated for 250-300 trials at varying color compositions and recorded. I hypothesized that the subjects’ perception of a given probe would be influenced by the relationship between the samples stored in memory. To test this hypothesis, the decision-making of subjects was evaluated under three conditions: difference in the sample red-green composition (ΔS) of 20, 30 and 40% (0.20, 0.30, 0.40). Each ΔS was tested with multiple probes. I predicted that decisions about the same probe would worsen as ΔS decreased. Logistic regression models (GLM) were used to fit the subjects’ decisions in the three ΔS conditions. Consistent with my hypothesis, the GLM slopes—measure of subject sensitivity to probe composition—increased as a function of ΔS , however, the magnitude of increase did not meet the benchmarks for statistical significance— suggesting that perceptual decisions are influenced by memory, but require deeper investigation.

Introduction:

For most of us, vision is the dominant sensation in our waking hours. Intuitively, we assume that visual perception is a process of representing what is out there in the world. But neuroscience has established that perception is actually the result of inferences made by the brain based on light information it receives from the eyes (Banich, M. T. *et al.*, 2018). If this is the case, then can our visual perception be influenced by other cognitive processes, such as memory? The driving question of this project is to study the relationship between working memory and visual perception. My goal was not only to investigate this relationship, but to determine whether this relationship is quantifiable. Utilizing methods from psychophysics and decision-theory, I aimed to investigate how perception of color is influenced by prior color information held in memory. By

quantifying the impact of human memory on color perception, my experiment can be used to further investigate and understand perceptual decision-making and its neuropathologies.

Related Work and Background:

This research belongs to a body of study known as psychophysics— the quantitative investigation of physical stimuli and their corresponding sensational and perceptual effects. The field was established by the German physician Ernst Weber, and later popularized by his pupil, physicist and philosopher Gustav Fechner. Together, their work has been immortalized as Weber-Fechner’s Law. Based on Weber’s initial study of the just-noticeable difference (JND) perceived when subjects were asked to lift items of increasing weight, Fechner concluded that the intensity of a sensation increases as a logarithm of

stimulus magnitude, rather than as a direct proportion (Fechner, 1966). Thus the initial applications of this field were restricted to the domain of sensation.

The development of theoretical frameworks such as Signal Detection Theory (SDT) helped extend psychophysics to the domain of perceptual decision-making. This extension has proven to be extremely successful in not only accounting for the decision-making behavior of humans and other animal models, but also in explaining how decisions are implemented by the activity patterns of neurons in the brain (Gold, J. I. *et al.*, 2007). This project attempts to leverage these decision-theoretic approaches from psychophysics to determine how perception is affected by memory.

To investigate perceptual decision-making, one must understand what exactly a decision is, and its discerning factors. Gold *et al.* (2007) define a decision as “a deliberative process that results in the commitment to a categorical proposition.” In many ways, decision-making is a form of statistical inference. How can the noisy background information provided by our sensory systems be broken down into its core values? And how can a decision-maker achieve a desirable outcome whilst avoiding undesirable ones? These questions form the basis of perceptual decisions.

Among the discerning factors of decision-making is reaction time. Sequential analysis (SA) is an extension of SDT, and assumes that in addition to the deliberative process of decision-making, there is also a time-commitment component. Success is not only dependent on achieving the desired outcome of the decision-maker, but doing so in a timely manner (Gold *et al.*, 2007). Additionally, SA incorporates a “termination rule”. We must make a commitment,

but are not governed by the immediacy of our senses or muscles— a “hallmark of cognition (Gold *et al.*, 2007).” By accounting for reaction time, SA has proven to be invaluable to psychophysical analysis. Thus I used its decision-making framework to quantify the effect of memory on perception.

Methodology:

Section 1A: Prototype Design & Game Logic

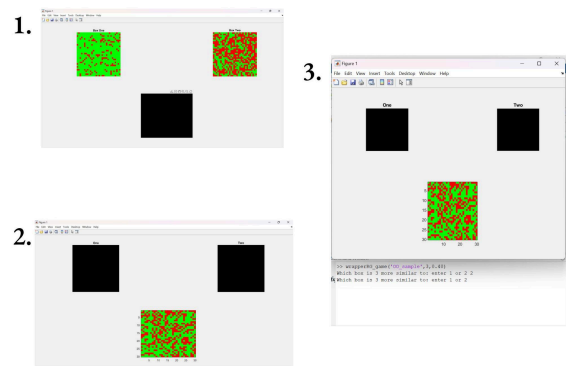


Figure 1: Prototype Design

The prototype design for the game was implemented in MATLAB programming language (1.) Subjects are first shown two samples. The samples appear for five seconds in this design before being covered with black boxes for one second. (2.) Then the probe appears. (3.) Subjects are given the opportunity to input their decision whilst still viewing the probe. Once their decision is recorded, the next trial proceeds. (Images of MATLAB program created by O. Odeboode).

The experiment is designed to be a tablet or computer game, accessible by web link. The basic outline, created in MATLAB (Figure 1), is as follows: subjects must make decisions regarding the red-green composition of two boxes (sample one and sample two). Using an RGB color system, I designed a program that chose a random number of pixels within an image to color red, the remaining then colored green.

Both samples appear next to each other on the same figure. There is a delay, allowing subjects to store

the image in their memories, before the samples disappear and are replaced with a final, centralized third image created with a red fraction at a value that falls between that of the samples. From there, subjects are asked which of the samples the probe is most similar to (Figure 1). This is repeated for the desired number of trials and relevant data is stored in a working table.

Section 1B: Javascript Application

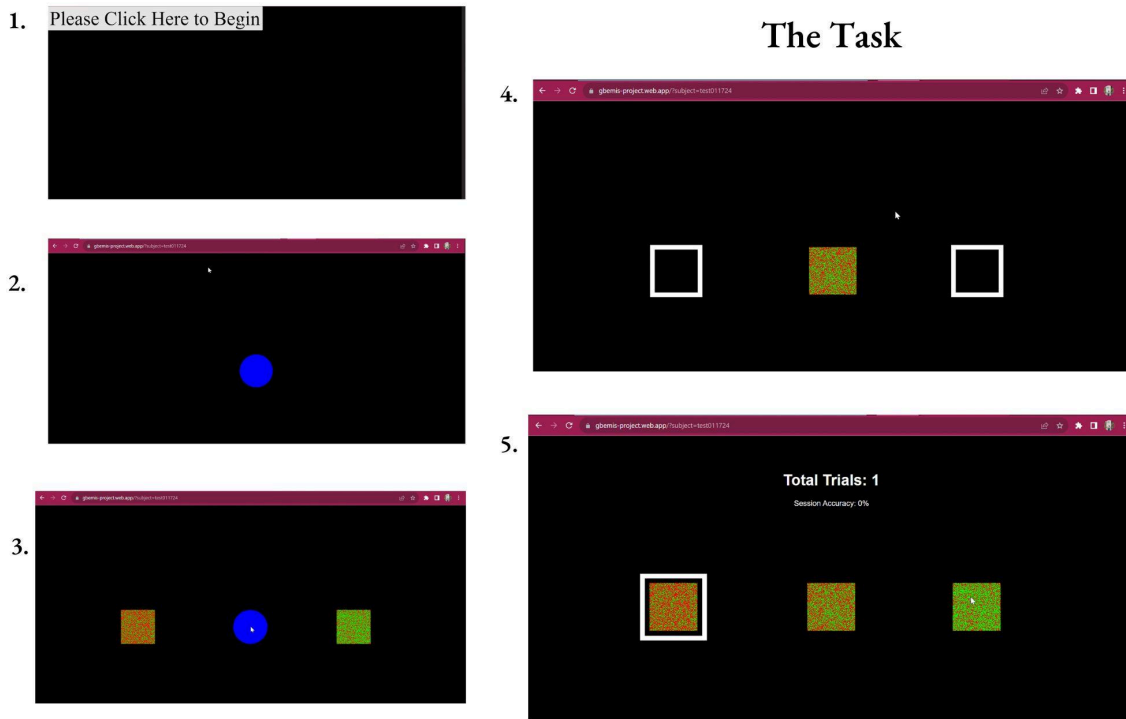


Figure 2: The Task

(1.) Subjects are given a unique link that allows them to complete the task on a web browser. The task does not begin immediately, instead requiring active participation. (2.) Between trials, subjects are presented with a circular, blue, “start button.” This allows them to choose when to begin the next trial, take breaks, and refocus on the task. (3.) Once the task begins, subjects are presented with the two samples for 750 milliseconds. (4.) The samples disappear and are replaced by a delayed centralized probe. Subjects are given unlimited time to make a decision about the probe in relation to the samples. (5.) After the decision is made, subjects are shown the correct answer (denoted by a white box), before the task proceeds to the next trial. (Images of Javascript program taken by O. Odebo).

The prototype, while theoretically functional, proved to be unfeasible for subject testing. MATLAB, while renowned for its matrix properties, pales in comparison to the web and app based strengths of Javascript. Encoding the same

game logic into Javascript enabled subject data to be collected across devices and stored in Dropbox. The app allows simultaneous data collection, as each subject is assigned a unique URL and corresponding configuration file, which provides

the input variables for the program. Dropbox then collects the data from each trial and stores it within a unique, subject-specific folder.

Among the issues addressed by the updated Javascript version of the game is the use of fixed sample and probe values. Beta testing of the MATLAB application found that randomly generated sample and probe values did not provide enough data to reliably fit decision models. Sample one and sample two needed to be at a set distance apart (ΔS), and the same probe needed to be tested across sample differences. Through iterative testing, a final set of sample and probe values were arrived at — ΔS values were set to 20, 30, and 40% (see Appendix). By retraining the number of unique trials, each option in the superset could be tested multiple times and have its data averaged from there. Each set has probes located $\pm 2\%$, $\pm 4\%$ and $\pm 8\%$ from the mean redness of the samples. For example, if $\Delta S = 40\%$, sample one could be 20% red, sample two 60%, and the mean redness 40%. Then, to create probes at $\pm 2\%$, the corresponding redness value would have to be at 38% and 42%—two percent more red than the mean, and two percent less. Additionally, the 30 and 40% ΔS sets have a $\pm 15\%$ from the mean. By testing the same probes across multiple ΔS values, the experiment quantified the impact of composition memory on significant data points. These supersets therefore replaced the need for a control group by creating a controlled variable across subjects.

For these trials, the sample duration—how long the subject can view the samples before they disappear—is set to 750 milliseconds. Additionally, the probe onset—the time in which no image is visible to give subjects time to store information in memory—is set to 400 milliseconds. It is with these values that the memory component of the task comes into play.

Section 1C: Live Experimentation

Data collection was split across two days—two 30 minute sessions. Each subject was tasked with completing 150 trials per session, totalling to a final collection of 300 trials. I chose to split data collection over two sessions to avoid the eye strain and mental fatigue associated with repetitive tasks. It must be recognized that there were avoidable, and unavoidable, flaws in data collection. Some subjects chose to perform the task independently of the group sessions, and others failed to complete the experiment. Subjects were motivated by the promise of a reward, in the case of this experiment, food and academic advantages.

Section 2A: Data Processing & Logistic Modeling

Each trial results in a data file containing its specifics. Once subject files were downloaded from Dropbox, they had to be converted from JSON files, which could be retrieved, into a MAT table for ease of analysis (see Appendix). All trials within a specific ΔS were then fed into another function that mathematically averaged the probability of a subject choosing the more red sample at each probe location. By using supersets, each trial, which is really a probe value within a specific ΔS , has an equal probability of being tested and is run multiple times. This data is then fed into a function that fits a generalized logistic model (GLM) of the probe location against the probability of choosing the more red option at each ΔS . These are then plotted on the sample graph to be further analyzed. Logistic modeling is preferable to explain binary perceptual decisions (red-green in this case) and has the logit (logarithm of odds) as a link function. For these reasons, I chose to fit the data with a logistic model.

Section 2B: Analysis & Interpretation Tools

The significance of subject performance could not be assessed from the GLMs alone. To investigate the correlation between memory and decision-making, data needed to demonstrate a consistent, predictable, and linear relationship. The GLM has two parameters that are fit: the β_1 and β_0 values. In a regression model, the function can be described with the following equation:

$$f(x) = \beta_0 + \beta_1 x + \sigma_M \tag{Equation 1}$$

where β_0 is the y-intercept of the graph, β_1 is the slope, and σ_M is the standard error of mean calculation. The GLM slope is a measure of subject sensitivity to dynamic stimuli. By extracting the β_1 value of each regression and graphing them against their respective ΔS values, one can make meaningful predictions and interpretations of subject data. It must also be noted that one subject's data had to be removed from subsequent analyses as they did not complete enough trials to provide reliable estimates of β_1 . The resulting database therefore consisted of twenty-eight subjects.

Results:

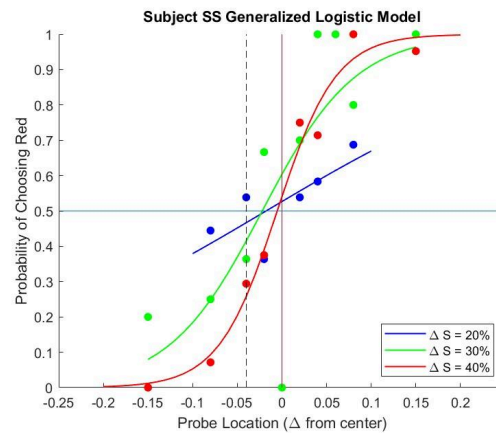


Figure 3: GLM of Subject SS

Each data point on the graph is representative of a probe (the tested value in the task). Through the use of supersets, the same probe location (distance from the mean redness of both samples) is tested at every ΔS . Although each probe at $x = \text{probe location}$ is the same distance from the average redness of its corresponding samples, subject performance differed at each ΔS , evidence of the effect of memory on perceptual decisions. (Figure created in MATLAB by O. Odebo).

To fully understand the impact of color fraction memory on decisions made during the task, probes across ΔS values needed a factor by which to be compared. This factor is the probe location. The probe location describes the red-green composition of each probe as a function of the initial two samples. By calculating the average redness of both samples and the distance of the probe from this mean in either the more red (+ x) or more green (− x) direction, subject decisions across ΔS values can be compared. Take, for example, probe location − 0.04 ($x = -0.04$) for subject SS. Each of the probe values is equidistant from the average redness of their respective samples, in the green direction, but as ΔS decreased, subjects were more likely to choose the more red sample during the task (Figure 3). If working memory had no influence on perceptual decision-making, subjects should estimate the

redness of each probe at the same probe location equally, rather than increasingly overestimating the redness of the probe as ΔS decreased.

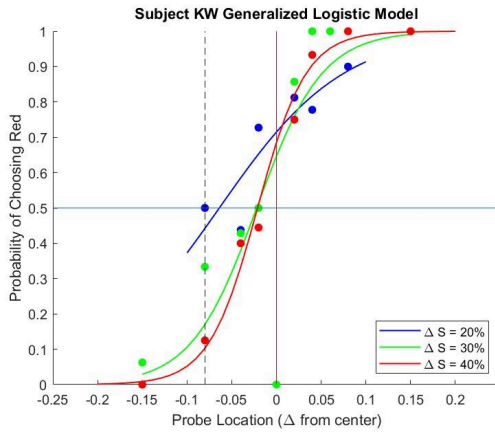


Figure 4: GLM of Subject KW

The location of the curves on the y-axis, known as the β_0 in statistics, is also indicative of an interesting trend in subject data, what I call the red-green bias. The y-intercept of this graph is (0, 0.78). There is a line at $x = -0.08$, demonstrating the skew explained previously. (Figure created in MATLAB by O. Odebo).

The GLM can also be used to determine the red-green bias of a subject. If a subject is unbiased, the β_0 – the y-intercept of the graph – should be close to zero. The further this intercept is from zero, the greater a subject’s red-green bias is. A positive β_0 value indicates a red bias, a negative β_0 , a green bias. Subject KW is a prime example of red bias. The curve of their graph intercepted the y-axis at $y \approx 0.78$. Regardless of the sample composition, subject KW would more frequently choose the more red sample during the task. All subjects demonstrated some amount of bias in either direction, but, interestingly, most had a slight red-bias. In order to affirm the relationship demonstrated by the raw GLMs of the subjects, I needed to investigate the analysis value – β_1 .

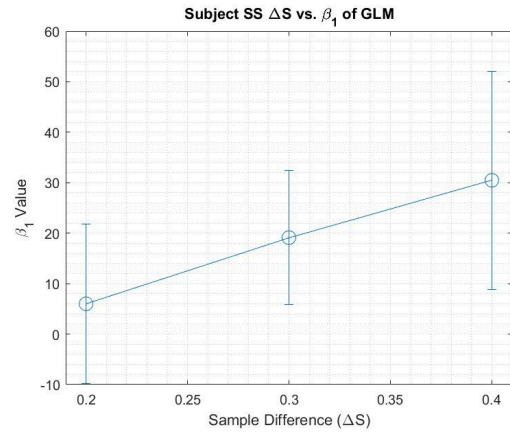


Figure 5 β_1 vs. ΔS Graph of Subject SS

Plot of the β_1 (coefficient of logit) of Subject SS at each ΔS , with standard error bars. The x-variable represents the ΔS value of tested samples, and as modeled by the GLM, the y-variable represents the β_1 value. In line with my initial hypothesis, Subject SS exhibited a trend of increasing β_1 as a function of ΔS . Note that the ΔS values are represented as decimals in all β_1 vs. ΔS graphs. (Figure created in MATLAB by O. Odebo).

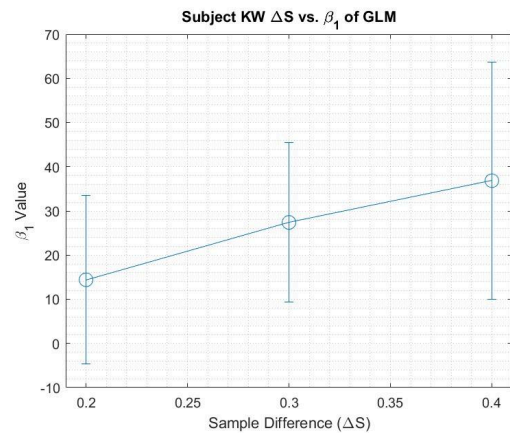


Figure 6 β_1 vs. ΔS Graph of Subject KW

Plot of the β_1 of Subject KW at each ΔS , with standard error bars. Subject KW also exhibited the hypothesized linear relationship, but to a lesser degree than that of Subject SS (Figure 5). Note that the ΔS values are represented as decimals in all β_1 vs. ΔS graphs. (Figure created in MATLAB by O. Odebo).

I first examined how β_1 values changed with ΔS for individual subjects. While there was

quite a bit of variation in this relationship, many subjects showed a trend of increasing sensitivity to the probe as a function of ΔS . Take, for example, Subjects SS and KW. From their GLM fits (Figure 3, Figure 4), it is clear that the slope of their choice function increases with ΔS . To better visualize this trend, I plotted the β_1 value as a function of ΔS for the two subjects (Figure 5 and 6). While the trend of increasing sensitivity as a function of ΔS is evident, the estimates of β_1 individual subjects are too noisy to draw a definitive conclusion.

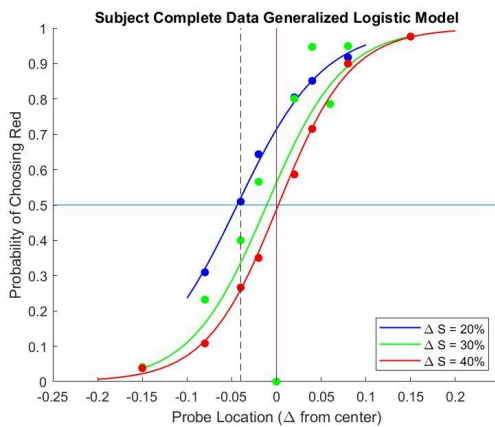


Figure 7: GLM of Complete Subject Data

Plot of all trials across subjects. As ΔS increased, the slope of the GLM also increased. Variability of subject performance resulted in a graph that exhibited the same relationship as Subjects SS and KW (Figure 3, Figure 4), but was too noisy to draw definitive conclusions from.

I tried two approaches to pool data from across the subjects. I first concatenated the data from all the subjects and fit it with a GLM (Figure 7). This combined data showed the same trend as the two individual subjects I highlighted before. However, due to the large variability across subjects in performance on the task, the estimates of β_1 were still too noisy to infer that the trend I observed was statistically significant.

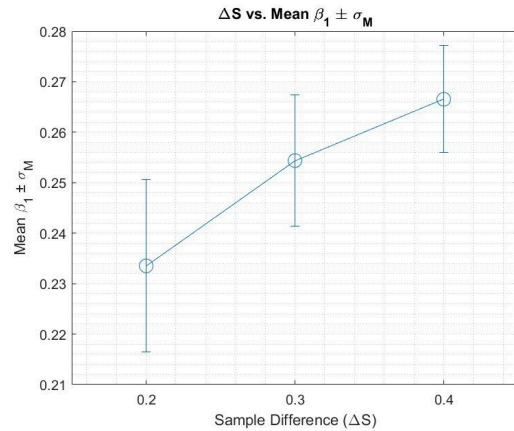


Figure 8: Averaged β_1 v. ΔS Across Subjects

Plot of the averaged $\beta_1 + \sigma_M$ across all subjects at each ΔS , with standard error (σ_M) bars. Note that the ΔS values are represented as decimals in all β_1 v. ΔS graphs. From left to right, the points are as follows: (0.2, 23.35), (0.3, 25.44), (0.4, 26.65), where the x-variable represents the ΔS value, and, as modeled by the GLM, the y-variable represents the β_1 value. The standard error for each β_1 estimate is as follows: 1.71, 1.30, 1.06% (see Appendix). (Figure created in MATLAB by S. Shushruth and O. Odebo).

I tried a second approach of looking at the mean of the β_1 values from the GLM fits of each subject. The average overall β_1 value at each ΔS and standard error of β_1 was calculated. This data is shown in Figure 8. The trend I hypothesized was seen with this analysis too. To test for the statistical significance of this trend, I performed a repeated measures ANOVA test. The result of the test ($p = 0.17$) did not reach the criterion for statistical significance. Thus, while the hypothesized trend appears robust, the inter-individual differences in the data set prevent me from concluding that the trend is statistically reliable.

Discussion:

The results of this experiment were interesting. Among individuals, performance across ΔS varied, but when all data was concatenated, the slopes generally improved as ΔS increased (Figure 8). While in line with the hypothesis— that the cognitive process of memory interfered with decision-making— the trend was not statistically significant enough to fully ratify the hypothesis.

By studying perceptual decision-making, I hoped to provide insight into our higher cognitive processing. The experiment encompassed a multidisciplinary approach, applying the computational nature of cognition to create a game-based experiment and perform the subsequent data analysis. The hypothesis; that human perception of color fractions is affected by memory was not definitively ratified or nullified. The expectation was that when the slope of the GLM for each ΔS would have a linear relation; that subjects' ability to distinguish color composition and make decisions about the samples would improve predictably as ΔS increased. However, the slope of each logistic fit, a measure of subject sensitivity to dynamic stimuli, when graphed against ΔS , did not create the perfectly linear relationship predicted by my hypothesis. While subjects did exhibit alterations in decisions due to the memory portion of the task, as exhibited by the spread of data points at the same probe location, statistical significance was limited. My results demonstrate a highly nuanced neurological relationship that merits further investigation.

There were a few points of contention in this experiment. Due to the amount of simultaneous data collection, the cache of a given trial might overflow, allowing some trials to be missed. JSON files containing multiple trials still

stored the relevant data, but it may be of interest to use stronger data storage programs. As with most human tasks, individual subject motivation varied greatly during live testing. This experiment relies on subjects who are motivated and attentive to performing the task. Uniformity in subject initiative and rewards at task completion are necessary for consistent data.

Either as a continuation of this project, or as additional research in the field, future experiments could benefit from larger sample sizes and a multitude of statistical examinations. It is of the single most importance for all future experimentation to address the “noisiness” of the data. As subject performance, innate talent, and motivation all vary greatly, further analysis and expansion of the existing database must keep these factors in mind. Additionally, it may be of interest to investigate the advantages and disadvantages of other statistical models, like power fits and logarithmic functions.

Conclusion and Next Steps:

Despite its inconclusive preliminary results, the data does raise a fascinating question. If human memory of color fractions has a promising impact on decision-making, is there a certain, quantifiable, range within which the impact is always significant? The partial ratification of my hypothesis is not a shortfall, but a starting point. This experiment's database of more than 7,500 trials has provided encouraging corollaries to explore.

Another factor that I would like to test in a continuation of this project is reaction time. Although this experiment applied the decision-making framework of sequential analysis (Gold *et al.*, 2007), I chose to focus more on the broader Signal Detection Theory. An indepth

exploration of the time-commitment component of perceptual decision-making will only serve to further the depth and range of my results.

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Appendix:

Link to Study Data and Code on GitHub

All analysis programs and subject data used in this experiment are linked to the following GitHub page:

<https://github.com/oodebode/PRSEF-2024.git>

If the link is no longer available, all information is publicly available under GitHub user @oodebode in the PRSEF-2024 repository.