DOES LOOKING MEAN LIKING?
A COMPARISON OF DECISION PROCESSES ACROSS
PERCEPTUAL AND PREFERENTIAL CHOICE

By

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ABSTRACT

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While both perceptual and preferential decision-making share the underlying iterative process of sampling and integrating information, it is difficult to make direct comparisons between these two types of decisions because they have been studied under separate disciplines, each with its own distinctive techniques. Research in perceptual decisions has highlighted how covert attention improves behavioral performance in a variety of sensory tasks, from contrast sensitivity and orientation discrimination (Liu, Abrams, & Carrasco, 2009) to motion coherence (Liu, Fuller, & Carrasco, 2006), as it enhances the processing of early visual information. Yet it has also been established that overt, relative attention, as measured by gaze exposure, is highly correlated with preferential choice in value-based decision making (Bird, Lauwereyns, & Crawford, 2012; Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Shimojo, Simion, Shimojo, & Scheier, 2003).

How do our higher-level intentions of being objective in perceptual choice versus being subjective in preference choice differentially impact choice formation? In this dissertation, I investigate how downstream decision processes, from information acquisition and evaluation to the eventual choice outcome, may be modulated by different task goals. In doing so, I explicate the role of selective attention in information search strategy, as it appears to have biasing effect in preferential but not perceptual choice. To compare choice formation in perceptual and preferential tasks, I used an experience-based paradigm that involved monitoring participants'

eye movements as they chose between two rapidly updating options (fishing ponds). Specifically, participants were asked to look at the two ponds and choose the pond they would rather fish from (preference frame), or choose the pond which had more fish surfacing on average (perceptual frame).

Results indicate that participants' eye gaze shifts toward the more favored option just before choice. However, this gaze bias was reduced in the perceptual frame. Moreover, perceptual participants maintained good discrimination accuracy even when they acquired less information. In contrast, preference participants were more likely to pick the option viewed for a relatively longer time, especially when less information was obtained. Data from both tasks are well described by a diffusion model of evidence accumulation which compares and integrates stimulus information based on eye gaze location, indicating a qualitatively similar choice process even when the higher-order tasks goals were different. However, consistent with behavioral results, the modeling reveals that distinction between task goals lies in quantitative differences across cognitive parameters as perceptual choice was associated with a lower gaze bias and greater information valuation than preferential choice.

As it is expected that higher-order intentions are reflected in downstream choice processes, I sought to test if this differential impact of task goals depended on the ability to actively control information uptake. This was done by conducting a second study that directly manipulated stimulus exposure by presenting samples of information in a single continuous stream. Results indicate that perceptual and preference participants were equally susceptible to the gaze bias when they passively viewed the options. Together, these results highlight the importance of agency and voluntary control of relative attention during the processes of information search and valuation across perceptual and preferential choice.

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CHAPTER 1: PERCEPTUAL VS. PREFERENTIAL CHOICE

LADY CAPULET.	Speak briefly, can you like of Paris' love?
JULIET.	I'll look to like, if looking liking move
	but no more deep will I endart mine eye
	than your consent gives strength to make it fly.

- Shakespeare, 1853, 1.3.100-103

In Romeo and Juliet (Shakespeare, 1853), Lady Capulet encourages Juliet to gaze at her potential suitor's face, take delight in his beauty, and in doing so, hopefully grow to like him and accept his love. Juliet, however, is skeptical. Ever cautious, she agrees to take a chance and look at her suitor, Paris, but in the same breath, vows to exercise restraint knowing that looking too deeply could render her vulnerable to a torrent of unchecked emotions.

In her statement, Juliet acknowledges that looking could lead to liking. Yet she also states that she will not easily succumb to the temptation of liking Paris by indulging in excessive looking. Instead, she is keenly aware that she is an autonomous being who can exert control over her own behavior in order to achieve the most desirable outcome for herself and her family. Thus, Juliet attempts to shield herself by wearing a cape of rationality while looking into the mesmerizing gaze of Paris' eyes. Can she maintain her original intention to resist being overly attracted, or is the alluring pull of the looking-liking bias too great?

More broadly, when we make decisions, how do our higher-level intentions hold up once we are thrown into a biased environment? The process of decision making involves the intermediate steps of devising a strategy to search and evaluate task-relevant information before making a final choice. How then, do our specific intentions pass on to downstream choice processes? In light of these questions, this dissertation aims to:

(1) Explore the generality of the overall choice formation process across different higher order intentions;
(2) Determine how diverging intentions are expressed in the information search and valuation stages as well as the eventual choice outcome; and
(3) Investigate how externalities in the environment that bias the choice landscape are accommodated by the original intention and its accompanying decision strategy.

The higher-order goals of being objective in perceptual choice versus being subjective in preferential choice provide a good example of diverging intentions that have been widely studied using different approaches across a variety of disciplines. Perceptual choice has been examined extensively in experimental psychology and the cognitive neurosciences using rigorous psychophysical tasks that require people to objectively discern the true state of the world by discriminating between sensory information. Conversely, preferential choice has been investigated in the social and decision sciences, with the focus on how people construct preferences depending on how they subjectively value specific attributes across several decision alternatives. While both perceptual and preferential decision-making share the underlying iterative process of sampling and integrating information, it is difficult to make direct comparisons between these two types of decisions because they have been studied under separate disciplines, each with their own distinctive techniques.

In this dissertation, I use an experience-based paradigm to study the three aims mentioned above by comparing processes across perceptual versus preferential choice. In doing so, I explicate the role of selective attention in information search strategy, as it appears to have biasing effect in preferential but not perceptual choice.

Perceptual decision making utilizes classical psychophysical methods that examine how people detect and discriminate noisy sensory information via measures of choice accuracy and response latencies. A common paradigm in perceptual decision making involves instructing participants to categorize noisy stimuli presented in series, for example, determining the overall motion direction of mixture of randomly and coherently moving field of dots (Gold & Shadlen, 2007; Kiani, Hanks, & Shadlen, 2008). It is assumed that participants arrive at a decision by serially sampling the evidence from the stimuli and averaging out the noise-driven fluctuations over time (Summerfield & Tsetsos, 2012). Hence, the extent to which noise is present in the stimulus provides a direct source of information that drives choice, and this relationship between stimulus discriminability and performance can be mapped using a psychophysical function.

In contrast to the focus on objective choice, preferential decision making investigates how people construct preferences depending on how they subjectively value the available decision options (Kahneman & Tversky, 1984; Usher, Elhalal, & McClelland, 2008; Warren, McGraw, & Van Boven, 2011). Stimuli tend to be static and perceptually unambiguous and uncertainty is not derived directly from external stimulus noise. For instance, in economic decision making tasks, participants typically choose between gambles with clearly labeled consequences such as the choice between a sure gain of $240 or a 25% to gain $1000 and a 75% chance to gain nothing; or choosing between two medical treatments where either 400 people would die or there is a 1/3 probability and a 2/3 probability that 600 people would die (Kahneman & Tversky, 1979). Here, uncertainty is derived from variability in the self-referential uncertainty about the expected value of each option. The focus on internal representations of value also extends to other types of preferential choice studies that are completely subjective: physical attractiveness, where participants typically view images of faces (Shimojo et al., 2003) or shapes (Isham & Geng, 2013) and food preferences (Armel, Beaumel, & Rangel, 2008; Schonberg et al., 2014).

Even though both tracks share similar goals of understanding the mechanisms of decision-making, researchers in both streams have been reluctant to import concepts or approaches from each other. As a result, it has been difficult to discern how people approach perceptual and preference choice differently because it is difficult to equate the methods used across the two disciplines. Do people intentionally pick a decision strategy leading to a more rational, objective answer when they are instructed to strive for perceptual accuracy? Furthermore, do people gravitate to other strategies when there is no objectively true answer in choices of preference? These questions bring up the distinction between choice outcomes and decision strategy. While an eventual choice may be compared against a benchmark optimal answer that maximizes accuracy in perceptual tasks or subjective utility in preference tasks, defining an optimal decision strategy is much less straightforward and less understood. How then do differences in higher-order intentions influence the specific strategies used? Given that how we allocate attention to the options in a choice set can be reflective of decision strategy, it is worthwhile to investigate if specific task goals impact how we control attention during information search and subsequently leads to potential differences in the eventual choice.

Role of Selective Attention in Decision-making

Selective attention impacts decision-making because it modulates the extent to which incoming decision information is processed. This is important because we have a finite amount of cognitive resources but are often immersed in a plethora of sensory stimuli. By enabling us to selectively prioritize certain aspects for further processing (Driver, 2001), attention governs how early perceptual processes can shape higher order cognitive demands like decision making.

What is not so straightforward is that the extent to which attention influences choice appears to be contingent on the nature of the decision task. For instance, in perceptual decision making tasks, selective spatial and feature based attention have been found to improve performance by enhancing the processing of early visual information processing (Carrasco, Ling, & Read, 2004; Liu et al., 2009, 2006; Pestilli & Carrasco, 2005) . However, it has also been established that attention, as measured by eye gaze exposure, is highly correlated with value-based decision making tasks which rely on participants' subjective preferences (Bird et al., 2012; Isham & Geng, 2013; Krajbich et al., 2010; Shimojo et al., 2003).

Attention in perceptual decisions. Attention is integral to perception as it is the "glue" that binds simple visual features into an object – a process necessary for effortful visual processing. Posner, Snyder, and Davidson (1980) systematically studied the effects of attention using their now famous spatial cuing paradigm. In their study, a cue is first presented to draw attention to a particular location in the visual field. The stimulus of interest is then presented after a short delay, which may appear with some probability at either the cued location or at some other location. Consequently, they found that people could more quickly detect a bright spot of light that was positioned in a cued location while maintaining accuracy. In a similar study, Bashinski and Bacharach (1980) found that attention is critical for detecting near-threshold stimuli as they show that people were more sensitive to a backward masked luminance stimulus when attention had been drawn to it by a cue.

This set of pioneering work on attention led to research on attention in perceptual decision making that identified the conditions where visual detection performance is enhanced by attention. It has been established that covert, voluntary attention improves behavioral performance in a variety of sensory detection tasks. Covert attention refers to attention that is deployed to a location in the absence of eye movements, and voluntary attention refers to endogenous attention that takes about 300 ms to be deployed, and can be sustained (Carrasco et al., 2004). The tasks include contrast sensitivity (Cameron, Tai, & Carrasco, 2002; Lee, Koch, & Braun, 1997; Pestilli & Carrasco, 2005), orientation discrimination (Carrasco et al., 2004; Liu et al., 2009), motion coherence (Liu et al., 2006) and spatial resolution (Yeshurun & Carrasco, 1999). Although most research has focused on visual attention, there is also evidence that tones are more easily detected when they are similar to an expected frequency (Scharf, Quigley, Aoki, Peachey, & Reeves, 1987), which illustrates that selective attention can also occur in the auditory domain.

In general, there is an extensive amount of empirical research highlighting that the orienting role of attention is necessary because it selectively prioritizes processing in the primary sensory cortices. According to Lu and Dosher (1998), attention to an object can lead to improved performance because external noise from distractors are selectively excluded from further processing, or because the signal-to-noise ratio increases within the attended stimulus. An increase in the signal-to-noise ratio can occur when attention enhances signal strength or when it reduces internal noise associated with processing the stimulus itself. Such increased stimulus sensitivity is considered a perceptual-level phenomenon that results from more efficient visual short term memory encoding. This can result from a gain in processing by increasing the rate of memory trace formation or from faster orienting, which reduces the delay before trace formation begins so that encoding occurs more quickly (Smith & Ratcliff, 2009).

Attention in preferential decisions. While much of the work in perception has focused on covert attention where participants are instructed to keep fixating on a central point in their visual field across an entire trial, researchers studying preferential decision making have focused on the overt orienting of attention instead. Overt orienting is the act of selectively attending to a spatial location over others by moving the eyes to point in that direction (Posner, 1980). The fact that eye fixations are easily tracked and considered as a good proxy for spatial attention has led to the well-known idea in preferential decision making that looking means liking. As such, researchers have sought to use eye movements to investigate the role of attention in preference construction.

The notion that eye movements are a passive index of personal preference is not new. Preferential looking has been used as a technique in developmental research to assess visual capacities and habituation in infants, with the assumption that infants prefer to look directly at stimuli that are visible and attractive to them (Birch, Shimojo, & Held, 1985; Fantz, 1965; Teller, 1979).

In studies of preference, options are presented at different locations and decision makers are allowed to freely view the images until they respond by indicating the option they think is the most attractive to them. The main empirical finding in these studies is that increased attention as measured by eye fixations on a particular stimulus image is correlated with a greater probability of subsequently choosing it. That is, if people fixate longer on a food item (Krajbich et al., 2010), novel black and white patterns (Isham & Geng, 2013), or faces (Shimojo et al., 2003), they are more likely to prefer the object and select it over another similar object. More specifically, people tend to start off by alternating looking at each option at the beginning with a roughly equal gaze distribution, before gradually shifting their gaze toward their favored option (Shimojo et al., 2003).

Given that most of this work is correlational, this brings up the question of causation: does overt attention guide the process of decision making in value based choice, or do we simply attend to items we already have a preference for? A recent paper suggests that eye fixations might do more than just reflect the output of an internal preference. Armel, Beaumel and Rangel (2008) manipulated attention by varying the relative visual attention across images of two junk food items (e.g. Snickers bar vs M&Ms) and asked hungry participants to choose which item they preferred, with the knowledge that they would receive the food item of a randomly selected trial. During a trial, the two food items were presented one at a time, on the right and left visual field, in an alternating sequence: one was presented for 300 ms, and the other for 900 ms on each alternation. This continued for six alternations so that the items were presented for a total of 7200ms. This pattern of alternations mimicked the process of alternating eye fixations in naturalistic settings and enabled Armel et. al. to manipulate the extent to which participants attended to each option. They found that junk food items were more likely to be chosen in the long fixation condition, and in a variant of this study, replicated their results with posters of art, suggesting that it is possible to bias preferences by manipulating the relative amount of stimulus exposure time across two options.

Overall, research specifically on attention has progressed along these respective tracks (Table 1): Work in perceptual decision making has focused on manipulating the locations of a pre-cue that orients attention in the absence of eye movements and examining how this impacts discrimination performance; conversely, research on preferential decision making has taken a more correlational approach in how the value of decision options that arise from internal preferences can be linked to overt attention placed on them during the deliberation process, as measured by the extent of eye movements and fixations. These differences in approaches make it hard to draw conclusions across both tracks, and determine if the role of attention really differs based on decision domain.

Table 1. Comparison between preference and perceptual tasks

	Preference	Perceptual
Task	• Subjective value o Face attractiveness, abstract art o Snack preferences • Relative choice between 2 options	• Objective answer o Sensory detection (contrast, motion, orientation discrimination) • Categorize a single option
Models	• Behavioral decision theory, experimental economics, neuro-economics, using mainly reports of choice preference (Huber, Payne, & Puto, 1982; Johnson & Busemeyer, 2005; Kahneman & Tversky, 1984; Zeigenfuse, Pleskac, & Liu, 2014)	• Experimental psychology and neuroscience, using rigorous psychophysical methods that examine behavioral accuracy, response latencies and neurophysiological data (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Laming, 1968; Ratcliff & Smith, 2004; Usher & McClelland, 2001; Vickers, 1979).
Attention	• Focus on overt attention. Manipulate the duration of stimulus presentation.	• Focus on covert voluntary attention, manipulated by an orienting pre-cue.
Fixations	• Free viewing paradigm • Eye fixations: passive measure of preference and attention	• Fixate on specific location (center) • Eye tracking to make sure that attention is covert (in the absence of eye movements)
Prediction	• Attention leads to greater likelihood of choice (biased choice).	• Attention results in more accurate choice (better discriminability).

Common Ground with the Flash Fishing Paradigm

Yet despite these differences, there remains a common structure to most of the decision making tasks implemented in both fields: people are instructed to observe and attend to one or more stimuli in a given sensory modality, integrate the information and then select a response which will maximize the probability of positive feedback or reward (Summerfield & Tsetsos, 2012).

Taking advantage of these commonalities, I sought to compare the processes underlying choice formation across perceptual and preferential choice by focusing on two broad stages: how people search and acquire information, as well as subsequently value and integrate the information. To do so requires an empirical paradigm that controls for the details across the two approaches beyond higher-level task goals. In order to accomplish this, I drew inspiration from the characteristics that differentiated the two approaches and developed a rapid, experience-based paradigm by combining their most distinctive features (Cheadle et al., 2014; Zeigenfuse et al., 2014). The resulting task used dynamic sensory stimuli and an attention cueing paradigm often found in rigorous psychophysical studies of perception, but, in the vein of subjective preference, does not place any restrictions on how participants sampled information by allowing them to freely view stimuli until they made up their mind. This is particularly advantageous as it provides a single experiment in which we can investigate what decision strategies people naturally use to fulfill the different goals of perceptual versus preferential choice.

In the Flash Fishing Task, participants chose between a left and right option consisting of a circular field of rapidly changing dots (updated every 50ms) sampled from an underlying distribution. They were told that each dot represented a fish on the surface of a circular pond, and they should look at the two ponds and choose the pond they would rather fish from (preference frame), or the pond which had more fish surfacing on average (perceptual frame). This allowed me to equate for expected value across frames. I also exogenously manipulated participants' initial attention with a neutral or peripheral pre-cue. Participants were shown the number of fish caught after each choice. In the preference frame, this was the next sample of fish that would surface in the chosen pond; and in the perceptual frame, the average number of fish present in the chosen pond. The number of fish caught was aggregated over trials and converted into a monetary bonus.

Such a design has several benefits:

(1) Free viewing paradigm. Unlike typical perceptual tasks that tightly control participants' eye movements, participants are allowed to look freely at the two options, which remain onscreen up till the point they make their choice, so that I can obtain their naturalistic viewing patterns and obtain top-down strategies of how people actively attempt to acquire information.

(2) Exogenous cue to draw attention. All of the studies reporting the link between fixations and subsequent choice were correlational, with the exception of a single study by Shimojo et. al. (2003) who directly controlled gaze duration by presenting two options sequentially, in an alternating fashion. They then directly manipulated the duration of stimulus presentation (long vs short presentations). In order to describe participants natural information search behavior, while striving to achieve a causal explanation of the gaze bias, I took a more moderate approach by leaving both stimuli onscreen, and presenting an exogenous pre-cue either in the center (neutral cue) or on the periphery (left or right), to draw participants' attention to a particular spatial location corresponding to the choice options at the start of each trial. This enabled me to see how a short burst of attention in the beginning affects subsequent search behavior.

(3) Option attractiveness is manipulated dynamically. Eye tracking studies of preference often display two static images that represent the choice options (e.g. picture of snack, faces from the Ekman database, abstract art) as part of the choice process. As these options are completely

subjective, preference is usually measured using self-report, by individually presenting the options to participants beforehand and asking them to rate the attractiveness of each item on a Likert scale. Instead of using static image representations, the options in the task consist of a dynamically updating image, whose value is represented by the number of dots. The dynamic and purely visual nature of the stimulus means that participants have to actively acquire information about the value of the options by looking and paying attention to the options. This means that tracking participants' eye movements opens a direct window into the process of information search, compared to when fixations in a task with static images like snacks and faces which carry comparatively less unique information and lead to information search focusing on the associated memories of the options the images represent.

Furthermore, this enables me to directly manipulate option attractiveness than relying on completely subjective self-reports of preference. Assuming that participants derive utility from option attractiveness (based on the mean number of dots in each option), I can determine how participants subjectively value each option by comparing their data with that of a perfectly rational agent who relies on expected utility as a benchmark.

CHAPTER 2: FLASH FISHING EYE TRACKING STUDY

The first study has several goals. A primary aim is to compare the process of choice formation – specifically, the stages of information search and integration – across perceptual and preference tasks. In doing so, I seek to replicate previous research by establishing that increased attention, as measured by mean amount of eye fixations, is correlated with choice in the Flash Fishing Task when participants are allowed to freely look between two stimuli options. In addition, this study examined how manipulating initial spatial attention using an orienting pre-cue can lead to differences in gaze duration across the two options, and subsequently choice. I expect that when the Flash Task is framed as a gambling or preferential choice, participants would be more likely to choose the attended option at the expense of accuracy (as measured by expected value) due to having a higher gaze bias. Conversely, in the perceptual condition, participants would be less likely to exhibit a gaze bias, and instead, would be more likely to choose the objectively correct option as participants would be more likely to ascertain the true value of the of the attended stimuli. Thus, I hypothesize that the correlation between looking at an option and eventually choosing it is stronger in the preference as compared to the perceptual task frame.

Method

Design. The study used a 2 × 2 × 5 mixed design: The task type (gambling vs perceptual) varied between subjects; an attention manipulation (neutral cue vs peripheral cue) varied within subjects across trials, and there were 5 levels of discriminability between options, which varied within subjects across trials. Discriminability between options was operationalized as the difference in the number of dots between options (mean number of dots in the right minus the left option: -40, -20, 0, 20, 40) made up from six combinations of option pairs.

Participants. A total of 61 participants (31 for the preference and 30 for the perceptual condition) were recruited from the Michigan State University community. They were paid $12 and a $1-5 performance bonus to take part in a single 1.5 hour session of the study.

Flash Stimulus. The stimuli were generated in MATLAB using Psychophysics Toolbox Version 3 (http://psychtoolbox.org/). Participants viewed two circular display options on an LCD monitor (Figure 5). Each display contained two fields of dynamically updating white dots on a black background with a diameter of 6.1° visual angle, with one located 6.75° to the left of a red central fixation and the other 6.75° to the right.

The dot display changed every 50 ms (20 Hz), and at each update, a new sample of dots was drawn from an underlying distribution and positioned at randomly generated locations within the circular field. There were four different display options to manipulate the number of dots shown in each sample: One option always had a fixed number of 130 dots while the other options had 110, 130, or 150 dots on average, and a standard deviation of 45 dots. These four options were factorially combined to yield six unique pairs of options, resulting in 5 difference levels in the mean number of dots between options that were randomly presented across trials. This will produce 3 levels of stimulus differences in the mean number of dots (0, 20 or 40 dots) presented. The location (left/right) of each option will also be randomly determined.

Procedure. Participants were assigned to either the gambling or perceptual condition when they arrived in a counterbalanced fashion. In the gambling condition, they were told to look at the two ponds and choose the pond from which they would rather fish from, or in the perceptual frame, they were to choose the pond that has more fish surfacing on average (full instructions in Appendix A).

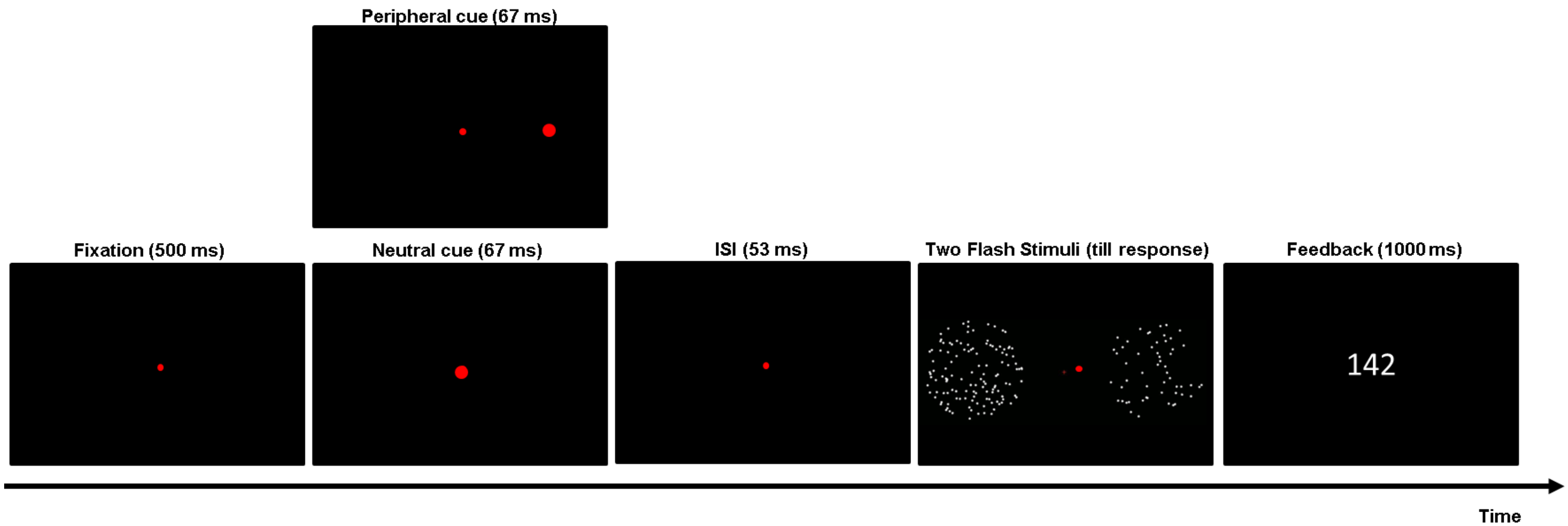

Figure 1. Stimulus presentation procedure in Study 1.

Participants first saw a central fixation point for 500 ms, followed by a larger exogenous cue for 67 ms which was designed to draw their attention to either the center or the periphery. After a short inter-stimulus-interval of 53 ms where the central fixation point was presented again, the two main stimuli appeared, and participants were free to look at the stimulus until they indicated which option they preferred via a key press. They then received feedback on how many fish they caught for that trial.

Participants then completed eight blocks of 90 trials (total 720 trials) of the Flash Task. During the task, the position of participants' right eye was recorded with the Eyelink 1000 system (SR Research, Ontario, Canada) at 500 Hz.

In each trial, participants start off by viewing a fixation dot for 500 ms in the center of the screen (Figure 1). Then an exogenous cue in the form of a red dot of 0.75° appeared either in the center (neutral cue: on 33% of the trials) or periphery (9° to the left on 33% of trials; 9° to the left on 33% of trials) of the screen for 67 ms. The cue was randomly located and had the purpose of either drawing attention to the center (neutral cue) or orienting participants' attention toward a particular option (peripheral cue). After a second fixation in the center for 53 ms, the two Flash stimuli will appear on the left and right. The stimuli were left onscreen until participants responded by indicating their choice by pressing a key (left option: "1" on number pad; right option: "2" on number pad) with their right hand.

They then received feedback about their choices. The number of dots in the option they chose at the time of the decision was displayed in white, at the center of the screen for 1000 ms. This was the number of dots that would have appeared in the next frame in the chosen option (gambling frame), or the mean number of dots in the chosen option (perceptual frame). The total number of dots was added across all the trials and scaled to give a bonus payout from $1-5 at the end of the session.

Pre-processing of Eyetracking Data. The raw eyetracking data (horizontal and vertical positions, and their respective times) was resampled every 25 ms (40 Hz) to produce two sets of eye movement trajectories over time: one was timelocked to stimulus onset and the other to the time of response.

The raw eyetracking data was grouped into saccades, where each saccade indicates a rapid eye movement between two fixation points. The saccades were detected using the "saccades" R-package (Malsburg, 2015), which relied on a velocity-based algorithm proposed by Engbert and Kliegl (2003). This enabled analysis of saccade-level details, including the number of saccades in each choice, as well as the dwell time and location of each saccade.

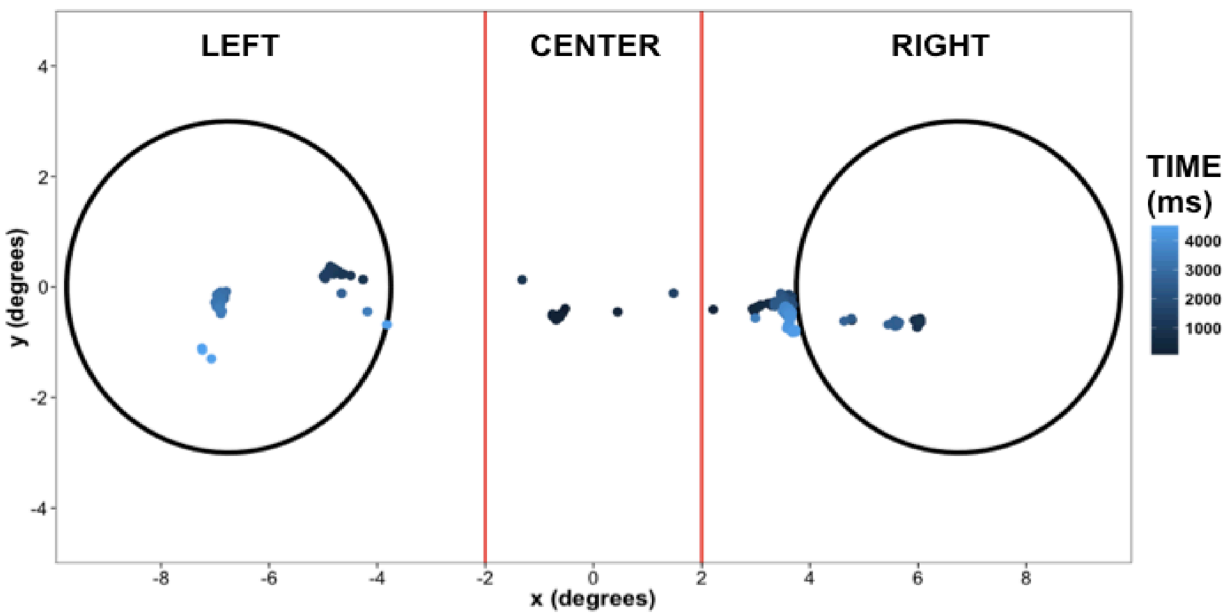

Figure 2. Sample plot of fixations in Study 1 for participant 105 on trial 17.

Each dot represents a fixation made every 25ms for a single trial. The red lines indicate the boundaries of location classification: left (<-2°), center (-2° to 2°) and right (>2°) on the horizontal axis.

The horizontal positions of the trajectory and saccade data were classified along 3 categories based on where they fell in relative to the center of the screen: the center, when the horizontal position was between -2 to 2 degrees; left, when the horizontal position was less than -2 degrees, and right, when the horizontal position was above 2 degrees. Figure 2 illustrates the categorization using the eye fixations in a single trial (participant 105, trial 17). It is worth noting that a significant proportion of fixations (*M* = 39.1%; *SD* = 12.0%, range of 8.72 – 75.3% across participants) did not fall directly on the two stimuli, especially at the beginning of the trial. In fact, a few participants had the predominant strategy of looking in the center. Hence, unlike other studies that omitted all fixations outside of the stimuli (Shimojo et al., 2003), I took a looser but more inclusive approach by using three broad categories: left, right, and center.

Relative gaze duration was then calculated as the proportion of time spent in each location by summing dwell times for each location across all the saccades in each trial, and dividing this by the total dwell time of identifiable saccades within the trial. On average, participants looked left 35.4% of the time, center 29.5% of the time, and right 39.2% of the time in each trial. The trials were also categorized based on the location of where people looked at the longest.

Analysis

The main analysis is divided into two portions. First I focus on describing how participants search for information by examining where people look, from when the two stimuli appear onscreen until the time they enter their choice response. Specifically, I focus on the choice reaction times which quantify the absolute stimulus gaze duration, as well as patterns of gaze behavior from eye tracking data, which measure relative spatial attention between the two options. After which, I show how both these measures of information search – the absolute and relative measures of gaze – affect subsequent choice.

Overall quantity of information acquired. To investigate how extent of information acquisition duration differed across manipulations, I ran a hierarchical general linear model with the overall speed of choice (1/RT) as the criterion, absolute task discriminability (coded as the absolute difference between the mean number of dots across options: 0, 20, or 40 dots) and task frame (perceptual coded as 1, gambling as 0) as fixed factors, and subjects as random factors. Participants made their choices more quickly ($b = 0.00907$, $p < 0.001$) as the absolute difference between option attractiveness increased, but did not have significantly different speeds between the gambling ($M = 1.41$ s, $SD = 0.66$ s) and perceptual frames (M = 1.56 s, $SD = 0.74$ s; $b = -0.261$, $p = 0.173$).

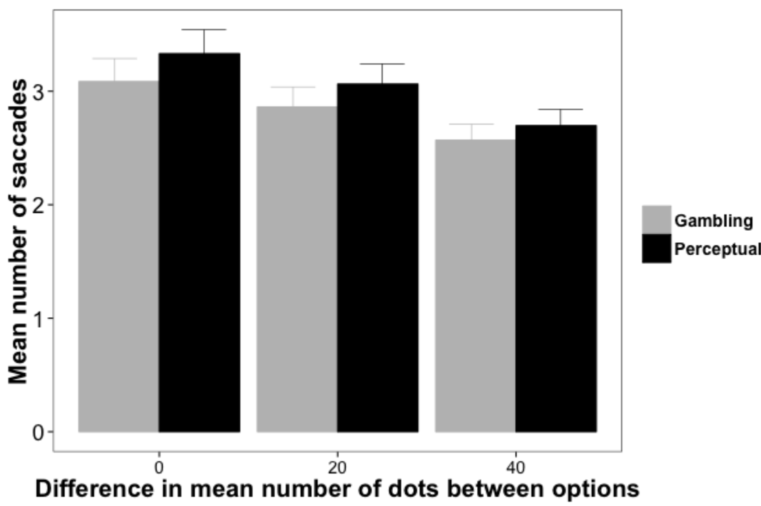

Figure 3. Mean number of saccades by option attractiveness discriminability in Study 1. Relative option attractiveness reflects task discriminability, as measured by the difference in mean number of dots between the 2 options) and task, with standard errors between participants.

A similar model was run with the total number of saccades in each trial as the predictor. Consistent with the results on reaction time, participants made fewer saccades as task discriminability increased (Figure 3, $b = -0.0128$, $p < 0.001$). This main effect, however, was also qualified by an interaction between discriminability and task frame ($b = -0.00326$, p =

0.007), indicating that the participants tended to make more saccades in the perceptual (*M* = 3.33, *SD* = 1.15) compared to the gambling (*M* = 3.09, *SD* = 1.11) frame when option discriminability was low, but this difference between the perceptual (*M* = 2.69, *SD* = 0.79) and gambling (*M* = 2.57, *SD* = 0.77) frames was attenuated when the options were highly discriminable.

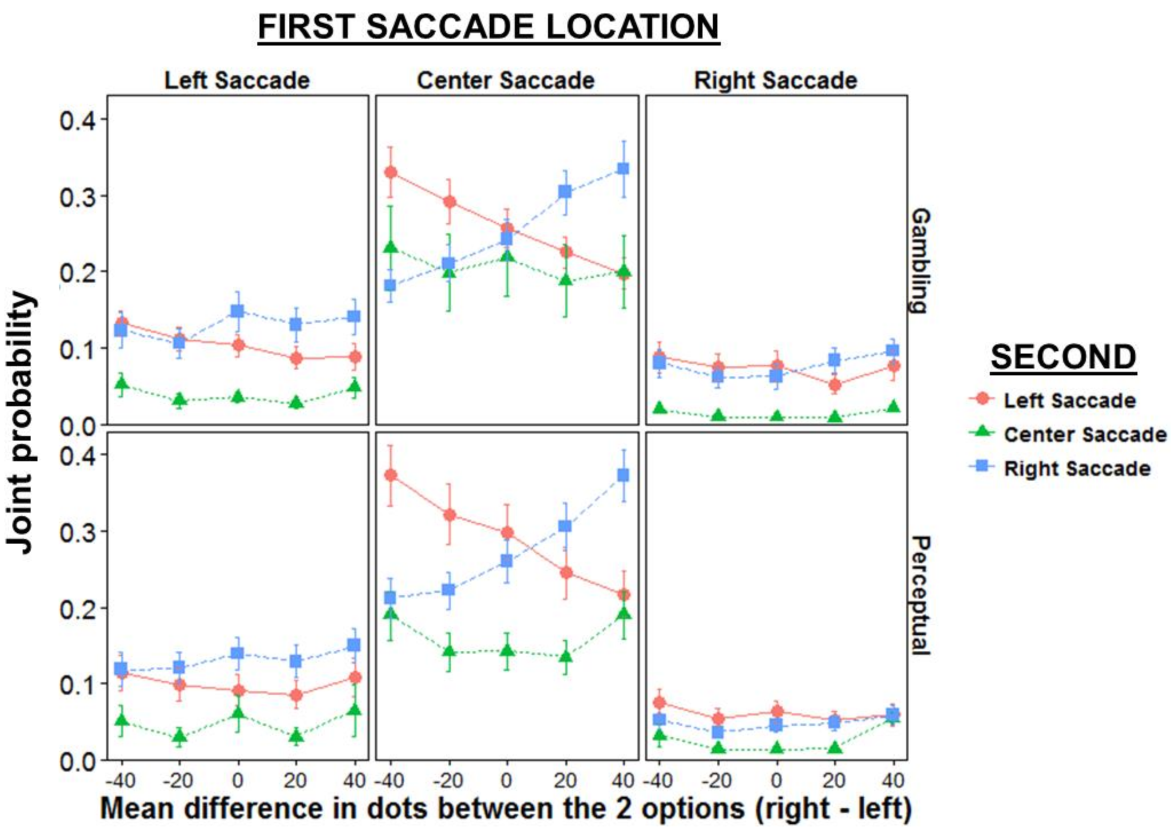

Figure 4. Joint probabilities of the first and second saccade.

Each point indicates the joint probability of making a saccade in two particular locations conditioned on each level of discriminability. The sum of the probabilities across the vertical panels within each discriminability level equals to 1, so each point depicts the relative probability of making one out of nine location combinations.

Patterns of information search. To get a better understanding of the information search stage in the decision process, I analyzed the gaze patterns of participants based on their eye tracking data.

As a first step to describe where people look, I calculated the probabilities of the first and second saccade made once the two stimuli appeared, that is, the joint probability of making a saccade in two particular locations conditioned on each level of discriminability (Figure 4). For example, the leftmost blue point in the top-middle panel indicates that the probability of making a center saccade followed by a left saccade in the gambling frame was 33.4% (standard error = 3.7%), given that the right option was extremely attractive when it had 40 more dots on average than the left option. The sum of the joint probabilities across the vertical panels within each discriminability level (the x-axis) adds up to 1, so each point depicts the relative probability of making one out of nine location combinations.

Overall, the analysis shows that participants exhibit two possible gaze patterns. Participants either start off attending to both options by looking in the center before gravitating toward the more attractive option, or they begin by looking directly at one option and then switching to the other.

The probabilities across the middle panels are highest across all three lines, implying that people are more likely to look at the center in the first saccade. Specifically, the probability of looking in the center is 13.6% higher than looking at the left option, $p < .001$, and 17.3% higher than the right option, $p < .001$. Then, they tend to look at the option that is more attractive in the second saccade. Within the center panels, the blue lines have a positive slope ($b = 0.0020$, $p < .001$), which indicates that participants are more likely to look from the center (first saccade) to the right (second saccade) as the right option becomes more attractive. The opposite occurs in the red lines, which have a negative slope (*b* = -0.0016, *p* = .001), indicating that participants look from the center (first saccade) to the left (second saccade) option when the left option is increasingly more attractive. Comparatively, people are less likely to make two consecutive saccades in the center (green lines; no effec3t of discriminability, *b* = -0.0003, *p* = 0.580), especially in the gambling condition (4.96% more likely to make two center saccades in the gambling than in the perceptual frame).

In the left panels, the relatively high but flat blue line highlights that people often look right after having already looked left. The red line is lower and has a negative slope (*b* = -0.00056, *p* = .0058), suggesting that people are less likely to make two consecutive left saccades unless the left option is highly attractive. Participants are unlikely to make a center saccade if they have already looked directly at one of the options. These patterns are mirrored in the right panels, implying that participants have an overall pattern of looking at the options in an alternating fashion, at least in the beginning.

The alternating pattern is corroborated in the Figure 5A, which plots the horizontal trajectory of eye gaze across the first 1.5s timelocked to the onset of the two flash fishing options. The trajectories are divided by the cue location, task frame and eventual choice, and illustrate how manipulating the location of an initial exogenous cue impacts the path of eye gaze. In the baseline condition when the neutral cue is presented in the center (green line), participants are most likely to start off by looking in the center, followed by making alternating eye movements first to the left and then to the right. The directional pattern could be indicative of the general familiarity from reading from left to right in most western written languages.

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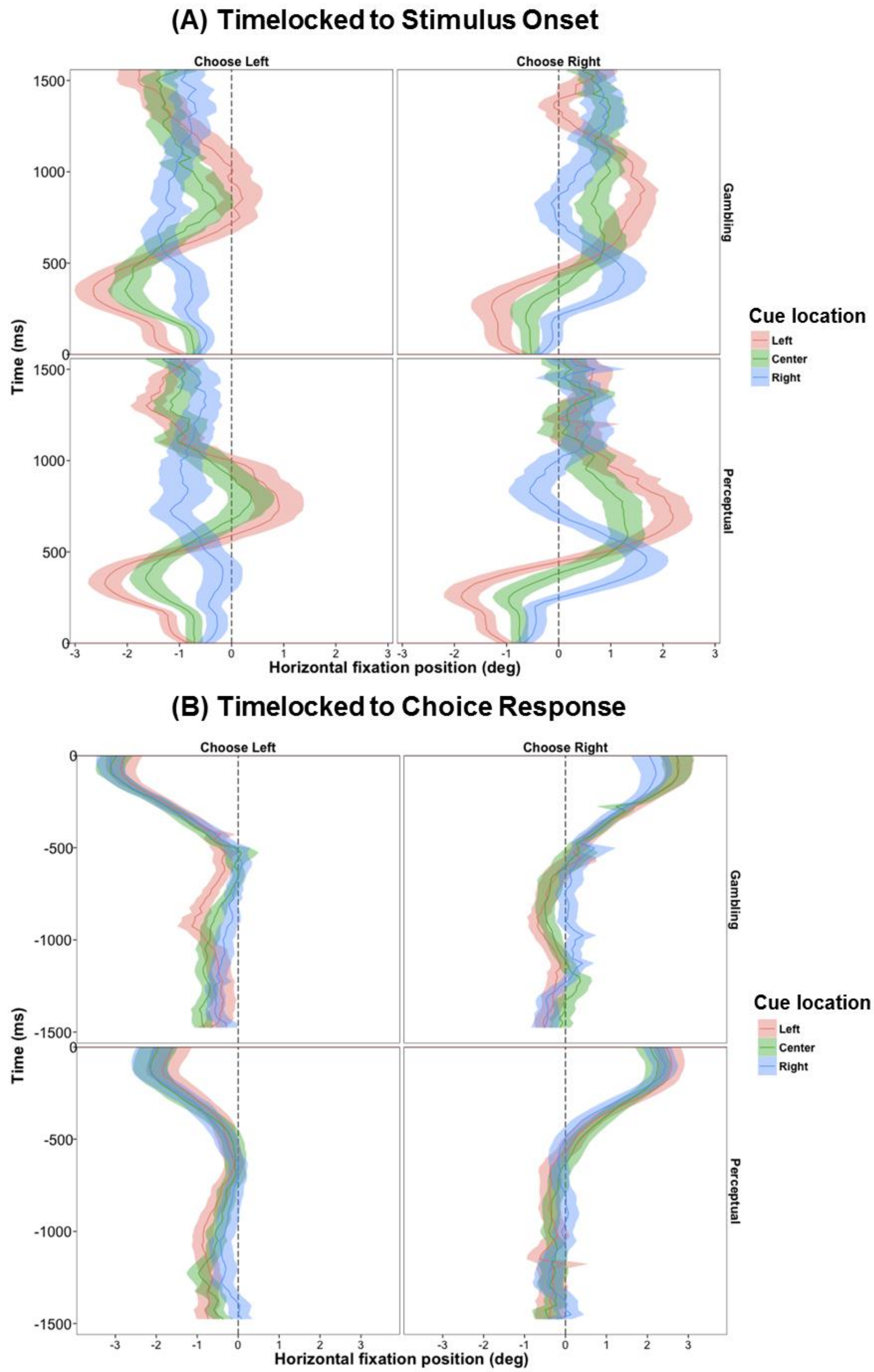

Figure 5. Mean horizontal gaze trajectories over time aggregated across participants.

The trajectories are for (A) the first 1.5s of the trial beginning from stimuli onset, or (B) the last 1.5s of the trial timelocked to the choice response. The colors indicate different cue locations.

Participants generally continue to follow this pattern when the left cue (red line) is presented, although they are more likely to make a leftward gaze at the start. The gaze pattern, however, differs slightly when the cue is presented on the right (blue line). Participants are much more likely to make a definite gaze toward the right in beginning of the trial when they eventually choose the right rather than the left option. This implies that the efficacy of the right cue, which goes against standard reading conventions, could be dependent on other factors like the attractiveness of the right option.

The mean inflection points in the paths tend to be more peripheral in the perceptual compared to the gambling frame across all the cueing locations, suggesting that participants are more likely to look at the options directly.

Moreover, the gaze trajectories show how people gravitate toward looking toward their chosen option. Such a gaze bias becomes even more apparent in Figure 5B, which depicts the same trajectories timelocked to the response. Similar to previous findings (Isham & Geng, 2013; Shimojo et al., 2003), participants seem to begin having a better than chance probability of looking at the option they subsequently choose about 0.5 s before the actual choice. The cues do not affect where participants look at the end of the trial.

To understand how the task frames directly impacts the extent of the gaze bias, I collapsed data across cues and calculated the overall likelihood of choosing the option participants currently fixated on (Figure 6). A hierarchical linear regression of choice likelihood on task type on the last 200 ms (last 8 time points, random effects across subjects) shows that participants have a 4.57% higher probability of looking at the eventually chosen option in the gambling rather than the perceptual frame ($p < .001$). This indicates that people in the perceptual frame are less likely to choose the option they are looking at just before they enter their choice response, implying that they viewed both items more equally.

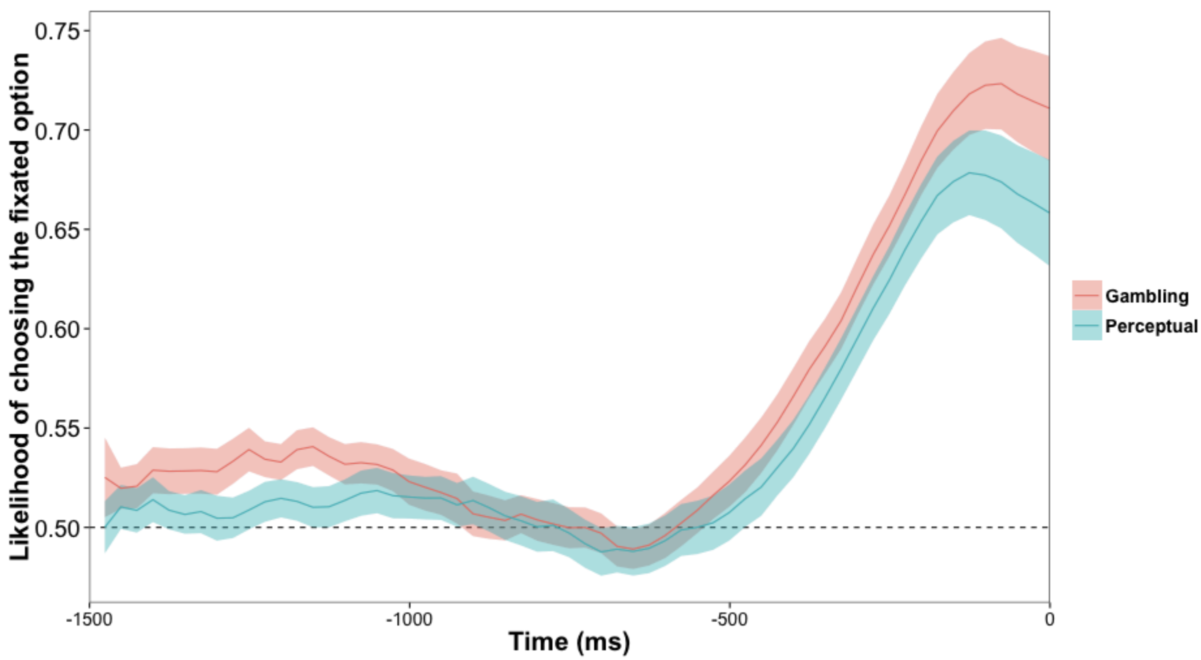

Figure 6. Mean likelihood of choosing the fixated option over time.

Data is aggregated across participants for the last 1.5s of the trial.

Impact of search patterns on choice. The first set of analyses – using eye gaze trajectories to reveal participants' information search procedures – was heavily influenced by previous studies of preference (Isham & Geng, 2013; Krajbich et al., 2010; Shimojo et al., 2003), and showed that their eye patterns of eye gaze seem to differ across task frames. Specifically, people made more saccades in the perceptual condition when it was difficult to discriminate between the two options, and also were less likely to look at their chosen option before choice. How then, do these key differences in absolute and relative gaze duration interact with the other manipulated variables like option attractiveness to lead to differences in choice? To further investigate their impact, I turned towards studies of perception for inspiration (Carrasco et al., 2004; Liu et al., 2009, 2006; Yeshurun & Carrasco, 1999), and examined the psychometric function of choice behavior.

Psychometric functions show the relationship of how a physical stimulus parameter, like the difference in the mean number of dots between options, affects the probability of a choice outcome, like choosing the right as opposed to the left option. I found that participants were more likely to choose the option that had, on average, a greater number of dots (Figure 7). The probability of participants choosing the option on the right against the mean difference in the number of dots between the two options was fit with a four-parameter Weibull function,

$$\Pr(\text{Choose Right}) = \gamma + (1 - \gamma - \lambda)\left(1 - \exp(-\frac{x}{\alpha})^{\beta}\right),$$

where α is the location parameter that identifies the point of subjective equality (PSE), β is the slope that characterizes the ability to discriminate between the two options from the steepness of the curve, γ is the upper asymptote and λ the lower asymptote.

Figure 7 investigates the effects of discriminability in option attractiveness, task frame, as well as the location of the option looked at the longest and the number of saccades made on choice. The addition of the last two factors was motivated by an attempt to quantify two variables that stood out in the earlier analyses of gaze patterns and choice reaction times: (1) the relative attention to the information across the two options (location of longest gaze) and (2) the absolute quantity of information acquired (number of saccades). To test specific characteristics of the curves, the choice data was fit using a hierarchical Bayesian model between subjects with these four factors. All the parameters described subsequently are group level estimates.

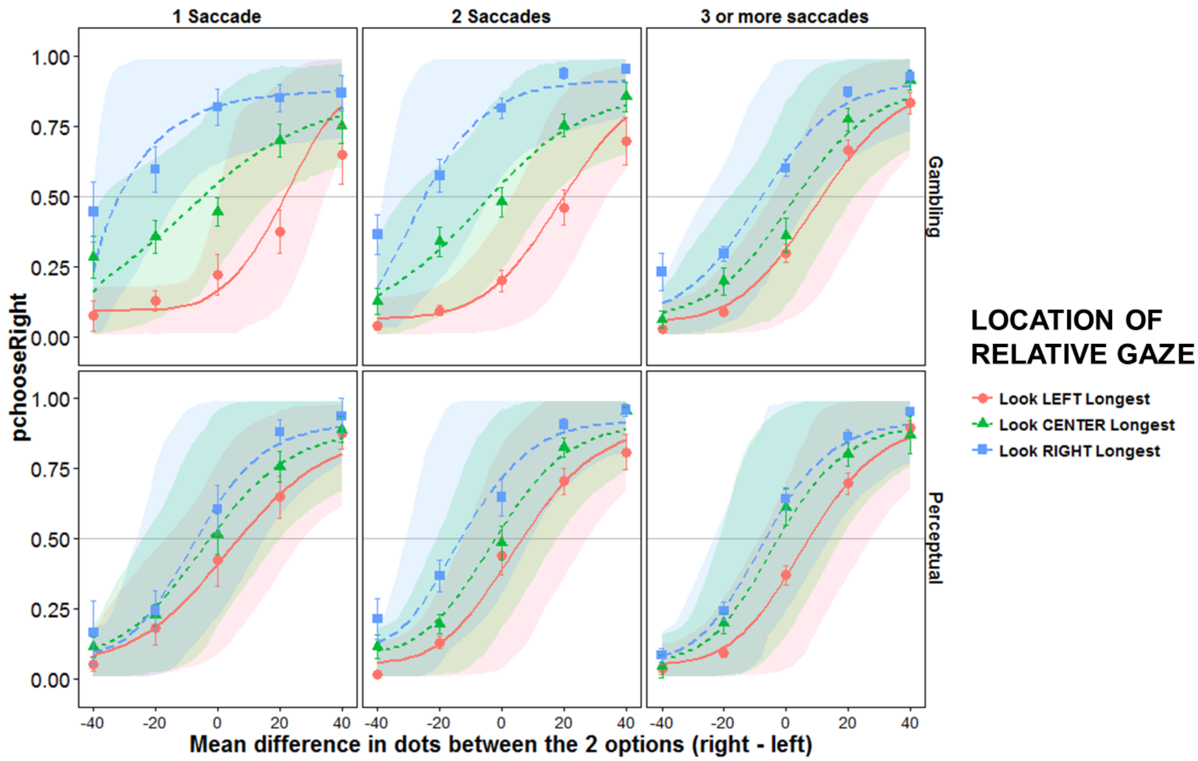

Figure 7. Psychometric curves describing the probability of choosing right in Study 1.

The probability of choosing the right option is plot against the difference in option attractiveness as characterized by the difference in the mean number of dots between the two options. The data was conditioned by the location of the option looked at for longest as a measure of relative gaze (color and shape) number of saccades as a measure of absolute gaze duration (vertical columns) and the task frame (horizontal rows). The error regions indicate the 95% HDI of the fitted model, and the error bars indicate the average within-subject standard errors.

On the whole, Figure 7 highlights the importance of relative attention on choice, especially in gambling trials with only one or two saccades. Each curve shows how the probability of choosing the right option increases as attractiveness of the right option increases. The bottom panels depict the psychometrics curves from the perpetual task frame. In all the three bottom panels, the three curves are mostly overlapping, indicating that gaze duration has little effect on choice regardless of the number of saccades made. To more accurately quantify the effect of disproportionately looking at one option over the other, I obtained the differences in the point of subjective equality (PSE) of the two curves when participants looked the longest at one option, compared to when participants looked in the center the longest. The PSEs indicate the value of relative option attractiveness when participants are equally likely to choose between the two options, that is, have a 50% chance of choosing the option on the right.

These contrasts (left minus central condition vs right minus central condition) are plot in Figure 8. Notice that all the black bars, illustrating the contrasts for the perceptual frame, are closer to zero than the grey bars, which correspond to the gambling frame. For instance, in the left minus center contrast in the 1 saccade condition (rightmost panel), the PSE difference in the perceptual frame (black bar) is 9.61 with 95% highest density intervals (HDI) ranging including 0 (HDI_{LOW} = -3.38 and HDI_{HIGH} = 22.6) dots depicted as error margins in the figure. This indicates that a single saccade made to the left option does not significantly affect the eventual choice in the perceptual frame.

This non-credible effect of gaze duration on choice is consistent across all but two of the other conditions in the perceptual frame: people were slightly more likely to pick the right option when they look at it the longest when they make two saccades, and people were slightly more likely to pick the left option when they look at it the longest when they make three or more saccades. On the whole, this pattern implies that the effect of relative gaze duration on choice is minimal in the perceptual frame.

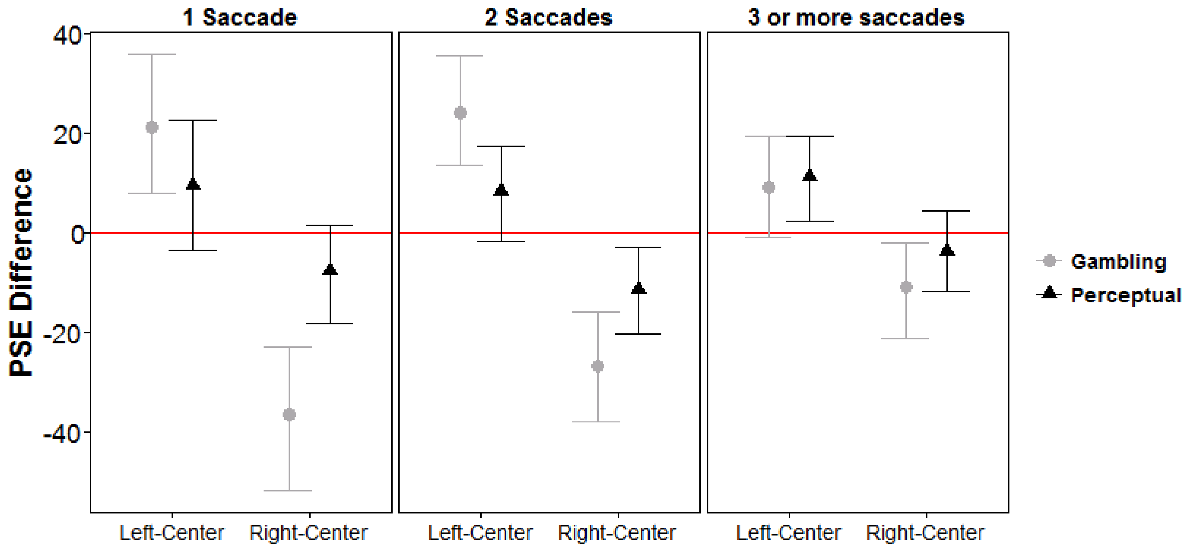

Figure 8. Point of subjective equality (PSE) contrasts in Study 1.

This plots the difference in PSEs between the curves when participants looked longest at the periphery (left minus central option vs right minus central option). The error bars show the upper and lower bound s the 95% HDIs. A contrast is considered credible when the HDI does not overlap with zero (red line).

On the other hand, the effect of relative gaze has a larger biasing effect on choice in the gambling condition, although the effect is attenuated by the overall gaze duration. In Figure 7, the blue and red curves are shifted to the left and right of the green central curve in the first two panels, suggesting that the people are more likely to pick the option they look at the longest when they make fewer saccades, but not when they made three or more saccades. The large horizontal shift in the curves led to large PSE differences, as shown by the longer grey bars in the first two panels of Figure 8. All four of these gambling contrasts in the first two panels were significant, but the two gambling contrasts in the last panel were not credibly different from zero.

To compare the effect of relative gaze duration on an option between task frames, I calculated the contrast between their corresponding PSE differences (grey minus black bars at each option location for each number of saccades in Figure 8. This quantified the extent to which the curves shifted to the left and right due to disproportionate viewing conditions, and in doing so, revealed that effect of task frame on relative gaze was mitigated by the absolute gaze amount. Specifically, the mean absolute difference in PSEs was 20.1 dots (HDI_{LOW} = 3.06 and HDI_{HIGH} = 43.7) when only a single saccade was made, the mean absolute difference was 14.4 dots (HDI_{LOW} = 0.39 and HDI_{HIGH} = 23.4) when two saccades were made, and the mean absolute difference was 7.3 dots (HDI_{LOW} = -6.64 and HDI_{HIGH} = 21.9) when three or more saccades were made. As such, the greatest difference between the perceptual and gambling frames occurred when only a few saccades were made, and participants' choice processes seemed to converge across tasks as they take more time.

Finally, I examined how the slope, which measures the ability to discriminate between the two options, changed between the two task frames. Figure 9 displays the difference in slopes (perceptual minus gambling) of the curves in Figure 7, by gaze location and number of saccades. Although there was no overall main effect of task frame on slope (Mean slope difference = 0.32, HDI_{LOW} = -7.16 and HDI_{HIGH} = 4.53), there was a slight trend of better discrimination in the perceptual condition in certain cases. In some of the first and second saccade conditions, people were better able to discriminate between the attractiveness of the two options in the perceptual than in the gambling task, as seen in the positive green and blue bars representing the center (Mean slope difference = 1.64, HDI_{LOW} = 0.30 and HDI_{HIGH} = 3.04) and right locations respectively (Mean slope difference = 3.26, HDI_{LOW} = 1.04 and HDI_{HIGH} = 5.90) when 1 saccade was made, and the positive green bar representing the center (Mean slope difference = 1.71,

HDI_{LOW} = 0.38 and HDI_{HIGH} = 3.23) when 2 saccades were made. All other contrasts did not differ significantly from zero, except in the left location when 1 saccade was made (Mean slope difference = -6.14, HDI_{LOW} = -10.4 and HDI_{HIGH} = -1.51). This last, negative difference is an anomaly, which could be due to a poor fit of the left gaze (red curve) in the single saccade, gambling condition (top-left panel in Figure 7).

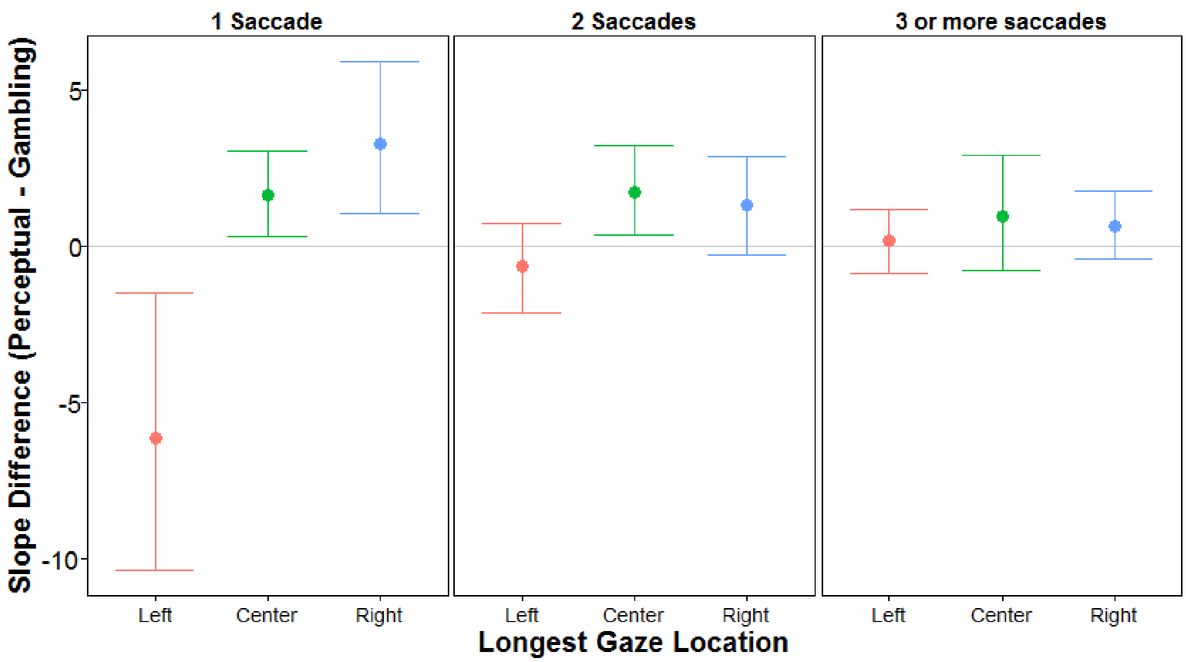

Figure 9. Slope differences between the task frames.

This plots the difference in slopes between the perceptual and gambling conditions at each location, conditioned on the number of saccades made per trial. The error bars show the upper and lower bound s the 95% HDIs. A contrast is considered credible when the HDI does not overlap with zero (red line).

Conclusions

To summarize, analyses of eye tracking data reveals that participants usually start by fixating in the center before looking at the choice options in an alternating fashion (Figure 4). The cue served to orient participants' attention and influence where they looked in the first two saccades (Figure 5). Although eye gaze was initially distributed evenly across the two options, participants' gaze subsequently shifted toward the more favored option, especially just before choice (Figure 6). This biased gazed pattern is consistent with previous findings in preference research (Isham & Geng, 2013; Krajbich et al., 2010; Shimojo et al., 2003). The bias was found not just the preference frame, but also in the perceptual frame, albeit to a weaker extent. Even though choice reaction times did not differ significantly between the gambling and perceptual conditions, participants were found to make more saccades in the perceptual rather than the preference frame when it was difficult to discriminate between the attractiveness of the two options. Together, these results suggest that different task goals prompt people to actively modulate their search strategy by adjusting the relative and total quantity of information acquired.

Further analyses revealed that the effect of relative gaze duration on choice was moderated by the total gaze duration as measured by the absolute number of saccades made (Figure 7). Behavioral findings highlight that participants were equally sensitive to the difference in expected reward between the options when we varied the mean difference in number of dots across perceptual and preference tasks; however, participants were heavily biased to choose what they were looking at in the preference condition. The strong effect of relative gaze was attenuated when more saccades were made in the gambling task, suggesting that participants are prone to like what they look when they make quick decisions with comparatively less information, but exhibit less of this gaze bias when they take more time to acquire additional information.

What then, is the underlying process that drives differences in the gaze bias? As a next step, I model the choice formation process formally to investigate if a single overarching framework may describe the general process of information search and deliberation, and how more fine-grained distinctions across the perceptual and gambling frames, like the gaze bias, may be manifested as differences in the specific cognitive parameters that lie within the framework.

CHAPTER 3: A COGNITIVE MODEL OF RELATIVE ATTENTION

The empirical findings in this study emphasize the importance of information search, a crucial part of the choice formation process that is often overlooked by many process models of cognition. For example, the well known Prospect Theory (Kahneman & Tversky, 1979) in behavioral economics focuses on how people first organize and reformulate existing prospects before subsequently evaluating them. Similarly, the Fast and Frugal Heuristics program and its associated Probabilistic Mental Model framework (Gigerenzer, Hoffrage, & Kleinbölting, 1991) highlights the mechanics of how people prioritize and draw inferences from a pool of cues that are already stored in their memory.

This assumption also forms the basis of many sequential sampling models, which have ignored aspects of information search in favor of describing how existing information is integrated over time. In general, sequential sampling models assume people accumulate information in support of the choice alternatives stochastically over time until a choice is made once the accumulated information passes a decision threshold (Figure 10). Where these models differ across perceptual and preference tasks is in the specific nature of the accumulation process – what type of information is processed, how the information is represented, and how the boundary is defined – depending on the domain of interest (Summerfield & Tsetsos, 2012).

Sequential Sampling Models in Perception vs Preference

Sequential sampling models have traditionally been shown to accurately predict choice and reaction time data in perceptual tasks, which involves making a statistical interference about the true state of the world from noisy sensory information (Gold & Shadlen, 2007; Liu & Pleskac, 2011; Smith & Ratcliff, 2009; Usher & McClelland, 2001).

In perceptual tasks, decision performance depends on the quality and quantity of information derived from stimulus processing (Ratcliff & Smith, 2004). Information quality is based on the objective properties of the stimulus and on the inherent variability of stimulus processing mechanisms in the central nervous system, while the quantity of information required before a response is based on the decision threshold set by the decision maker.

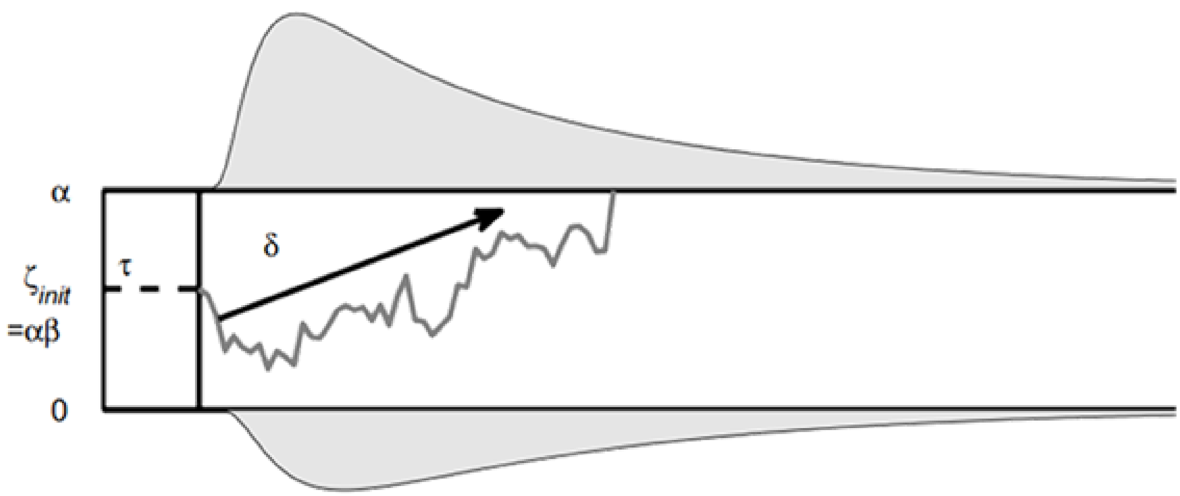

Figure 10. Drift diffusion model as adapted from Wabersich & Vandekerckhove (2014). This shows the stochastic process of evidence accumulation toward threshold α, beginning at starting point bias β, with drift rate δ and non-decision time τ.

More recently, sequential sampling models have also been used to describe preferential tasks (Busemeyer & Townsend, 1993; Krajbich et al., 2010; Krajbich & Rangel, 2011; Litt, Plassmann, Shiv, & Rangel, 2011; Zeigenfuse et al., 2014). While models of perceptual decision-making emphasize that decisions are made in a strictly optimal fashion, sequential sampling models of preference assume that people accumulate internal information about the subjective value of the decision alternatives. Uncertainty is derived from variability from these subjective values rather than from stimulus noise. These values are sampled stochastically from internal processes like memory, and may be actively constructed during the deliberation process based on long-term memory traces from past experiences (Sigman & Dehaene, 2005) or newly sampled outcomes from a recently attended option (Busemeyer & Townsend, 1993; Diederich & Busemeyer, 1999).

Models of preferential choice also highlight capacity limitations within the deliberation process and show how the role of attention places constraints on evidence accumulation. Decision Field Theory (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001) proposes that evidence across options are sampled in parallel, but only from the attended attribute. Attention might be oriented stochastically, or directed preferentially to a subset of the information provided, such as the most valuable attribute. By addressing how attention impacts choice, Decision Field Theory is able to account for phenomena like preference reversals, such as the Allais paradox (Johnson & Busemeyer, 2005), and contextual effects in multi-attribute choice (Roe et al., 2001).

Where most sequential sampling models fall short, however, is that they do not consider how information is sampled across the decision options. Hence, these models are unable to account for choice biases due to differences in the relative duration of eye gaze between options. To address this, Krajbich and colleagues (Krajbich et al., 2010; Krajbich & Rangel, 2011) proposed a model which incorporates eye gaze as a direct measure of attention. Unlike Decision Field Theory, where sampling occurs in parallel across options even when attention is directed only toward a particular attribute, this model assumes that decision makers accumulate a relative decision value across objects over time based on the option that a decision maker’s eyes are fixated on. Specifically, the rate of evidence accumulated in favor of one option (drift rate) at any given instance is proportional to the weighted difference between the values of the fixated and unfixated items, where the weight discounts the value of the unfixated item relative to the fixated one. Indeed, they showed that this model well accounted for eye tracking data from a food preference task where participants were allowed to look freely between two food images, providing further support that overt attention, as measured by eye fixations, contributes directly to the evidence accumulation process during deliberation in value-based choice.

Drift Diffusion Model with Relative Gaze

Thus, the ability of sequential sampling models to accurately describe the cognitive processes of choice formation in perceptual and preference tasks reinforces the idea that these two types of choices are structurally similar because they share an underlying evidence accumulation process. This is advantageous as the deliberation process of choice may now be distilled into several cognitively meaningful parameters, including payoff sensitivity as measured by the drift rate, response caution as measured by the decision threshold, and an initial bias toward one option over the other.

However, despite these similarities, the models have been conceptualized and studied under separate experiments in previous research. This makes the current empirical study especially interesting because it provides a basis for quantifying commonalities and differences across data across perceptual and preference tasks. In particular, I examine whether the two tasks are indeed structurally equivalent by investigating if the data may be modeled via a single sequential sampling model, and how more quantitative differences across tasks may be revealed by the specific parameter estimates across tasks, but within the same overarching model.

One main question of interest here concerns the underlying mechanism in how the main attention manipulation, the initial exogenous cue, affects choice. To put it more succinctly: how does the cue work? One possibility is that the cue directly leads people to choose the cued option – a simple priming effect. Another plausible explanation, consistent with the empirical finding that the lateral shift in PSE when choice is conditioned on the most viewed option, is that the cue only influences where people look at initially. In doing so, the cue makes people disproportionately view the options when they quickly make a decision, and it is this disproportionate viewing process that leads to the ultimate effect on choice behavior, especially in the gambling fame.

Parameters. Testing these hypotheses requires a model that can quantifies both the effect of a simple, initial bias toward the cued option, as well as the relative gaze duration between the choice options. Thus, I took inspiration from Krajbich et. al., and modified the classical drift diffusion model by incorporating data from eye-gaze into the drift rate. The resulting model of attention contained the following parameters:

- Non-decision time τ, the time where participants are not deliberating between the two options (e.g. time used for motor activity, inattention), ranging from 0.1 to 1.0 s.
- Threshold α, a measure of response caution as it is an index of the amount of evidence necessary to make a choice, ranging from 0.1 to 5.
- Bias β, the initial propensity to choose the option on the right side of the screen. This ranges from 0.1 (strong bias for the left option) to 0.9 (strong bias for the right option), so 0.50 indicates that people are unbiased.
- Drift rate, δ, the rate of evidence accumulates in favor of the right option in each trial,

$$\delta = s\,[\mathrm{g}_{\mathrm{RIGHT}}(\mathrm{v}_{\mathrm{RIGHT}} - \theta \cdot \mathrm{v}_{\mathrm{LEFT}}) + \mathrm{g}_{\mathrm{CENTER}}(\mathrm{v}_{\mathrm{RIGHT}} - \mathrm{v}_{\mathrm{LEFT}}) + \mathrm{g}_{\mathrm{LEFT}}(\theta \cdot \mathrm{v}_{\mathrm{RIGHT}} - \mathrm{v}_{\mathrm{LEFT}})\,],$$

where g is the gaze proportion of looking at a particular location (right, center or left) across an entire trial, v is the value of the left or right option as measured by its mean number of dots, s is a multiplying parameter from -5 to 5that scales the overall drift, and θ is the fixation weighting parameter from 0 to 1 indicating the extent to which the fixated option contributes to evidence accumulation. When θ is 0, evidence is accumulated from the fixated option only (gaze bias), but when θ is 1, both options contribute equally to the evidence accumulation process (classical drift diffusion model).

This model is a simplification of that proposed by Krajbich and colleagues, as this is order invariant and only requires the gaze proportions and option values to be aggregated across each trial, rather than requiring the moment-to-moment gaze locations and option values at each time point. In addition, it incorporates central fixations by making the assumption that people attend to both options such that they equally contribute to evidence accumulation. This is unlike the model by Krajbich et. al., which relied on eye fixation data that corresponded to the left and right option locations only.

Moreover, the model by Krajbich et. al. was only applied to studies of preferential decision making. By extending this model to both task frames, I make the claim that the process of perceptual choice formation is in essence, based on the same principles as preferential choice. This makes the crucial assumption that main source of evidence in preferential choice, the subjective valuation of option attractiveness, has a direct relationship to the more objective information about the sensory characteristics (the average number of dots onscreen) in perceptual choice. The difference in how people value each piece of evidence is quantified by the drift scaling parameter, and now can be compared across perceptual and preferential choice.

Moreover, this model was developed as a hierarchical Bayesian model with participant-level and group-level estimates. This in contrast to the model by Krajbich et. al. who relied on simulation to fit and evaluate it. Such a hierarchical instantiation of the model is particularly advantageous as it allows for error variance to be pooled across participants to yield group-level estimates which can be more directly quantified and tested across conditions. It also produces participant-level estimates similar to the model by Krajbich et. al., which can then be used for further investigation of individual differences across participants.

All of the parameters except non-decision time (single value only throughout all conditions) were allowed to vary across the initial cue location, as well as the task frame (perceptual vs preference) conditions. The parameters were estimated using the JAGS Wiener module (Wabersich & Vandekerckhove, 2014), an extension for the Just-Another-Gibbs-Sampler (JAGS) in R.

Hypotheses. Given that there was no difference in the choice reaction times across tasks frames and cueing conditions, I anticipate that the estimated values of the threshold and non-decision time to remain similar over all the conditions, suggesting that people, on average, accumulate similar amounts of information before making their choice.

How the bias and fixation weighting parameters vary across conditions is more of an open question, as these are not directly addressed from the empirical results. Recall that people were more likely to choose the cued option. If this phenomena is due to a simple priming effect of the peripheral cue, it is expected that there would be no initial bias when the neutral cue was positioned in the center, but there would be a positive bias when the cue drew attention to the right option and a negative bias when the cue drew attention to the left option. Moreover, if the effect of the cue was stronger in the gambling frame, then the absolute value of bias would be higher in the gambling compared to the perceptual condition.

However, if the differential effect is of the cue is actually driven by the relative gaze, the underlying process would be reflected in the fixation weighting parameters of the drift rate. The minimal effect of relative gaze duration in the perceptual condition could be due to a fixation weight of close to 1.0, which would imply that people weight both the left and right options equally regardless of where they look such that their process of evidence accumulation approximates the classical drift diffusion model. In contrast, the fixation weight would be lower in the gambling condition, suggesting that people tend to discount the information from the non-attended option when they are instructed to choose the option they prefer.

Finally, the drift scaling parameter indexes the overall rate of evidence accumulation. Consistent with the finding that the slope of the psychometric function was generally higher in the perceptual frame across most of the conditions, the drift scale is likely to also have a higher value in the perceptual rather than the gambling condition. If this is the case, it means that people place a greater value on each piece of information in the perceptual compared to the gambling condition.

Classical Drift Diffusion Model

To test contribution of accounting for relative gaze duration, the attention model was pitted against the classical drift diffusion model, which was also modeled hierarchically in a similar fashion. Likewise, the classical model included similar bias, threshold, and non-decision time parameters. However, unlike the attention model, the drift rate was not based on eye movement and option attractiveness. Instead, two drift parameters were estimated, the:

- Baseline drift rate, the rate at which evidence accumulates in favor of the right relative to left option over time when both options are at the same level of attractiveness; and
- Drift sensitivity, the rate of increase in drift rate per level of increase in the mean number of dots in the right option. This is an index of sensitivity to the mean difference in number of dots between the two options.

Modeling Results

Model fits. The Deviance Information Criterion (DIC) was used to compare the two models. As a hierarchical modeling generalization of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), it shares their characteristics of considering goodness-of-fit and penalizing for model complexity. The attention drift diffusion model (DIC = 145456) was found to provide a superior fit to the data than the classical drift diffusion model (DIC = 150289). This highlights the importance of accounting for attention based on where participants are looking onscreen, a consideration that many cognitive models, like the classical drift diffusion model, neglect even though the models deal with incoming evidence in the visual domain.

Parameter estimates. The estimated group-level parameters of the classical and attention drift diffusion models are presented in Figure 20 (more details in Appendix C) and Figure 11 respectively. In the attention drift diffusion model, the fixation weighting parameter was uniformly high in the perceptual frame varied (Figure 11A, Mean = 0.931,HDI_{LOW} = 0.838 and HDI_{HIGH} = 0.990) across all the cueing conditions, indicating that the effect of relative gaze duration on choice was minimal. As expected, the fixation weighting parameter was lower in the gambling condition, and the values were also more varied (Mean = 0. 749,HDI_{LOW} = 0.584 and HDI_{HIGH} = 0.922). Thus, there was general trend of a slightly higher weighting parameter in the perceptual compared to the gambling condition, but the main contrast effect did not reach a point of credibility (Mean slope difference = 0.18, HDI_{LOW} = -0.012 and HDI_{HIGH} = 0.371), possibly due to the large variance in the gambling frame. The pairwise contrast between the task frames was credible in one (the left) out of the three cueing conditions (Mean left slope difference = 0.20, HDI_{LOW} = 0.017 and HDI_{HIGH} = 0.383).

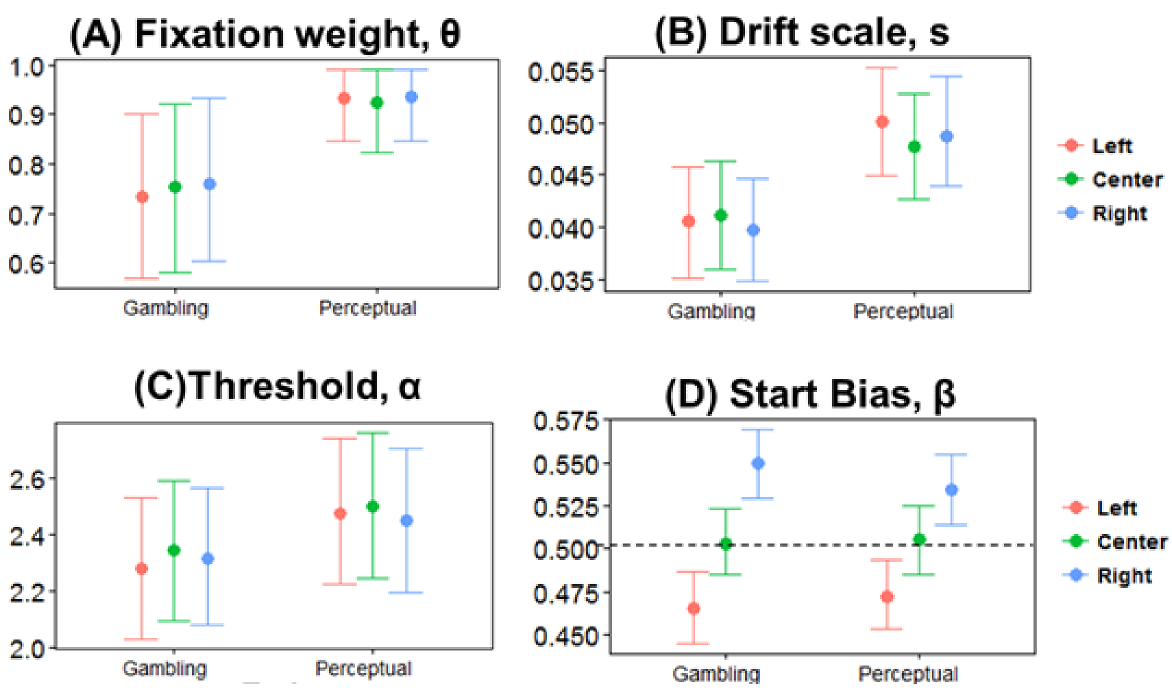

Figure 11. Parameter estimates of the attention drift diffusion model for Study 1.

There was a main effect of the drift scale in the attention model (Figure 11B, Mean drift difference = 0.0084, HDI_{LOW} = 0.0003 and HDI_{HIGH} = 0.0159), indicating that participants generally accumulated evidence faster in the perceptual compared to the gambling condition. The thresholds remained equal across all conditions (Figure 11C). Finally, the estimates of bias yielded similar results to that of the classical model: the peripheral cues significantly biased choice in the left and right gambling condition, and in the right preference condition.

Conclusions

In summary, computational modeling of the difference in option attractiveness, eyetracking gaze durations, choice reaction times, and choice outcomes, reveals the importance of accounting for patterns of relative attention, as measured by the location of eye fixations. The attention drift diffusion model provides a more comprehensive picture of the choice formation process: by linking patterns of information search to the subsequent process of information valuation, as reflected by the drift scaling parameter. These findings are consistent with previous research (Zeigenfuse et al., 2014), and suggest that people may differentially value information from the choice options depending on the specific, higher level instructions.

More generally, the modeling shows that perceptual and preferential decision making share the same general process of evidence accumulation. But, it also demonstrates some critical differences across the two higher-order task frames: the effect of the cue biasing choice corroborates with the shift in PSE due to relative gaze in the empirical results, and suggests that the biasing effect of the cue appears to have less of an effect in the perceptual compared to the preference condition.

The presence of the gaze bias in a naturalistic paradigm highlights how voluntary, relative spatial attention to an option is correlated with choice. Modeling also explains the underlying basis of the gaze bias as it reveals that participants disproportionately weight option information based on their fixations such that information derived from an attended option has a greater contribution toward choice.

As a next step, I developed an empirical study to examine if there is causal link between gaze and choice. Does directly controlling attention to each option lead to similar biases in both tasks? The process of doing so would also change the type of attention involved – from voluntary, relative attention across two options presented simultaneous at different locations, to non-voluntary, dedicated attention when the options are presented one at a time– would this largely wipe out the differences between perceptual and gambling task frames?

CHAPTER 4: DIRECT MAINPULATION OF RELATIVE GAZE

It is expected that higher-order intentions are reflected in downstream choice processes. This was shown to be the case in the first study, as the instructions to pick the option with the most dots on average in the perceptual condition, or to pick the option they preferred in the gambling condition, induced differences in how participants actively searched for information, as well as how they valued the contents of the information acquired.

This active, voluntary nature of taking action to meeting a goal is typical in many aspects of behavior. We often consciously and actively strategize how to carry out certain action with the purpose of fulfilling a higher-level need of some sort (Aarts & Elliot, 2012; Duncan, Emslie, Williams, Johnson, & Freer, 1996; Rotter, 1960). Yet what happens when we are no longer able to plan out a strategy for achieving a goal, but instead, have to contend with passively absorbing a stream of goal-relevant information? This is very much akin to having to look up and list out pros and cons of a particular course of action, compared to watching a video that presents all the arguments of interest.

Given that research in learning and problem solving has emphasized benefits and contributions of an active approach toward the pursuit of academic goals, for example, performance in a test to demonstrate mastery and comprehension of the material learned (Benek-Rivera & Mathews, 2004; DeNeve & Heppner, 1997; Haidet, Morgan, O’Malley, Moran, & Richards, 2004; James et al., 2002), I sought to test if this differential impact of task goals depends on the ability to actively and voluntarily control information uptake.

Apart from directly addressing the above question, the second study has the additional purpose of controlling for several limitations in the first study. Firstly, the first experiment aimed to provide a comprehensive investigation on how attention affects perceptual and preferential choice in a free viewing paradigm. However, opting for a more naturalistic study duration led to several trade-offs: gaze duration was only indirectly manipulated with an initial exogenous cue, eye gaze was always accompanied by a movement (saccade), and gaze duration was also conflated with the quantity of information sampled.

An initial concern was that the optional stopping paradigm, while serving as a good baseline to describe how participants naturally behave, could have weakened the attention cuing manipulation. Previous studies in perceptual decision making show that covert attention drawn by a peripheral cue lasts for approximately 150 ms (Carrasco et al., 2004). This duration was considered relatively short given that participants determined the overall gaze duration and choice time. Indeed, we find that the cue impacts gaze location in the first two saccades, but its effect on the overall gaze duration weakens as information search lengthens. This is because people make tend to look at both options in an alternating fashion so the relative gaze duration across options evens out when they make more saccades. This leads me to believe that the influence of the initial orienteering cue on choice was largely mediated by relative gaze duration.

Hence, I directly manipulate relative gaze by presenting stimuli in varying durations in the next study. The variables chosen in the main four-way interaction (between tasks, option attractiveness discriminability, relative gaze via the option viewed the longest and absolute gaze duration via the total number of saccades) was not a set of analyses I predicted a priori, and instead, was informed by the patterns of information search. As I did not anticipate conditioning the data on so many variables where two of which were intermediate outcome variables, that set of analysis was definitely underpowered. Thus, as a next step, it is prudent to directly manipulate relative gaze in place of using an intermediate measure of gaze proportion, which would vary across trials and participants. Making this change would lead to greater experimental power, and should result in a stronger effect that occurs even when the total information search process is lengthened.

Directly manipulating relative stimulus exposure would also give me grounds for making the causal claim that relative gaze can impact choice, which goes beyond the correlational relationship found in the first study. Recall that the first study utilized a free-viewing paradigm where I did not impose any restrictions on how participants looked at the two stimuli options. This led to the finding that people acquired and integrated information differently across perceptual and preference tasks. What then happens when attention is no longer relative and voluntary? In the second study, the options are presented one at the time, so participants are expected devote their full attention to the single dynamically updating option onscreen. Thus, the study has the additional purpose of examining if differences in higher order goals replicated even when participants' do not have the ability to control the process of information search across competing options.

Another issue in the first study is that both options were presented simultaneously on the left and right, so participants were likely to make a saccade every time they shift their attention from one stimulus to another. Research in embodied cognition suggests that cognition is situated in activity (Anderson, 2003; Wilson, 2002), such that the act of making an eye movement is also a factor that could influence choice. The study by Shimojo and colleagues (2003) supports this view, as they find that faces presented for a longer duration were more likely to be judged as more attractive only occurred when an eye movement was made towards the faces when they were presented on the left and right, but not when the faces were centrally presented. In a different paradigm, Schonberg and colleages (2014) found that the value of food items can be manipulated by instructing participants to view a stream of food images and asking them to make a simple motor response when they hear an irrelevant tone. Subsequently, participants were more likely to prefer items that were presented concurrent with the motor response, implying that motor actions have an underlying influence on preferential decision making.

To test if the motor action of making a saccade was the underlying factor that impacted choice in the first study, I used centrally presented stimuli in the study and instruct participants to keep their eyes fixated on a fixation point in the middle of the stimuli throughout each trial. This enables me to see if the effect of manipulating gaze remains effective without any lateral eye movements.

Thus, unlike the first study, which was more free-form as it aimed to describe how people searched and valued information in a naturalistic setting; the second study has the goal of being a more controlled attempt to examine how exposure duration can cause a bias across perceptual and preferential choice. It address alternative explanations like motor movements, and investigates how people respond to the different task frames when they are unable to voluntarily control information search.

Method

Design. The study had a 2 × 5 × 5 mixed design: the task framing manipulation (gambling vs perceptual) varied across participants; 5 levels of difference in mean attractiveness across options similar to study 1, and 5 stimulus duration levels (33%, 50%, 67%, and 75%) over 8 unique combinations of conditions outlined in Table 2.

Stimuli of the two options were similar to that of the first study in all aspects except for the color and location. The stimuli were presented sequentially in the center of a computer screen. One option consisted of blue dots and the other red dots so participants could easily distinguish between the options. The brightness of the colored dots was roughly equated in a short pilot test by taking the average values of four test participants that completed a luminance equalization routine using a staircase procedure.

Table 2. Stimulus duration levels in the second study.

ID	**Number of switches**	**Number of Frames**				**Duration of First Option**
		Total	**Set 1**	**Set 2**	**Set 3**	
1	1	16	8	8	0	50%
2	1	24	8	16	0	33%
3	1	24	16	8	0	67%
4	1	32	16	16	0	50%
5	2	24	8	8	8	67%
6	2	32	8	8	16	75%
7	2	32	8	16	8	50%
8	2	32	16	8	8	75%

The 8 option combinations enabled me to control for several other factors across the levels of gaze duration. Thus, the number of options switches varied between 1 (e.g. red, then blue option or vice versa) and 2 (e.g. red, blue, then red option again) and the number of frames during each presentation was set to either 8 or 16. These two factors meant that the total number of frames in each trial was also manipulated (16, 24 or 32 frames). Finally, the order of colors (blue or red option first) was counterbalanced across trials.

Participants. In total, 63 (31 gambling and 32 perceptual) undergraduate participants from MSU psychology subject pool took part in the study. In addition to receiving course credit for participating, they also earned a $1-5 bonus based on their task performance.

Procedure. The study was held over a single 2-hour session. Similar to the first session, participants were randomly assigned to either the gambling or perceptual condition and received instructions for the actual flash task with two central stimuli: a red pond and a blue pond.

The instructions were similar to that outlined in the first study (Appendix A). In the perceptual frame, participants were asked to choose if the red or blue pond had more fish on average, while in the preference or gambling frame, participants were asked to choose if they preferred the red or blue pond.

In a trial (Figure 12), after displaying a central fixation dot for 500 ms, the flash stimuli (the two colored ponds) appeared in the center of the screen. The two options were presented in a sequential, alternating fashion, for example, participants would first view a stream of blue dots updated every 50ms, followed by a stream of red dots at the same speed, and on occasion, a second stream of blue dots. They were told that the dots represented blue or red fish from only two ponds, so they could consider all blue fish, even if they appeared later, to be from the same pond. Participants were also instructed to wait until all the fish were presented, and that they should immediately make their choice once the fish disappeared and were replaced by a central fixation point. The fixation point remained onscreen until participants pressed a key (labeled in red or blue) to indicate their choice, which was recorded, along with the reaction time.

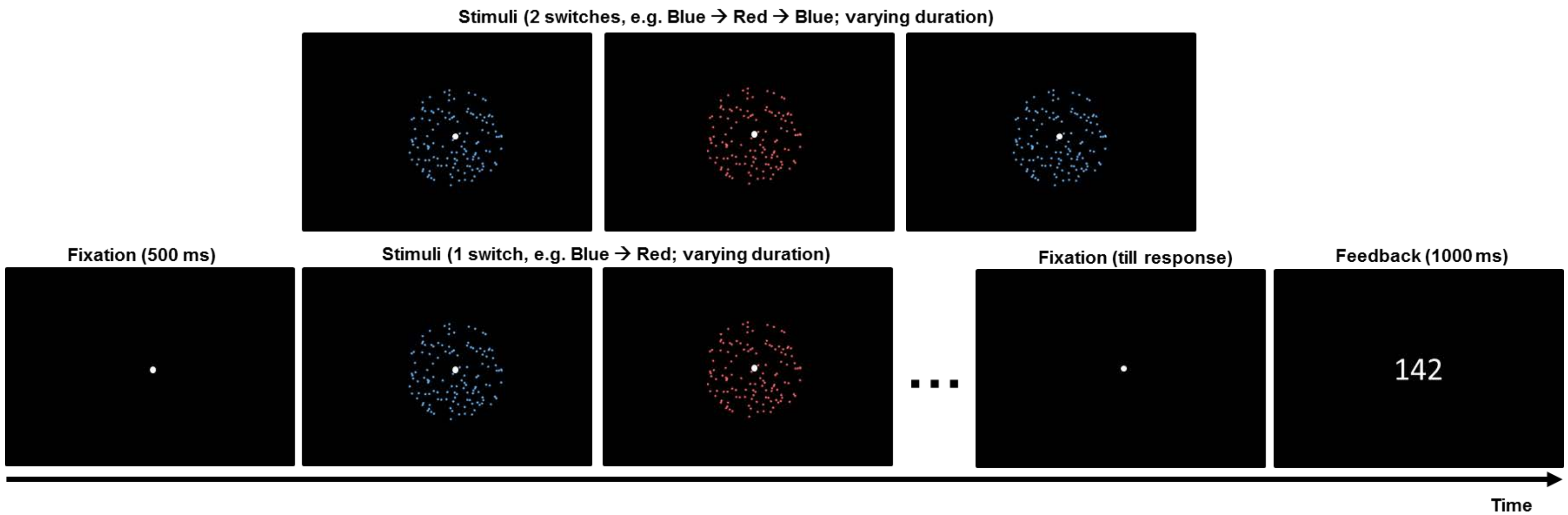

Figure 12. Stimulus presentation procedure in Study 2.

After a central fixation for 500 ms, the two stimuli were presented in an alternating sequence. Participants then made their response immediately after the sequence ended and saw a central fixation point again until they made their response. They then received feedback in terms of the number of fish caught in that trial.

Similar to the first study, participants earned points by catching fish, which was displayed as feedback at the end of the trial. The points were aggregated and scaled to generate a $1-5 performance bonus paid at the end of the session.

Analysis

Overall quantity of information acquired. I examined if participants followed the instructions to respond immediately after the stimulus stream ends (Figure 13).

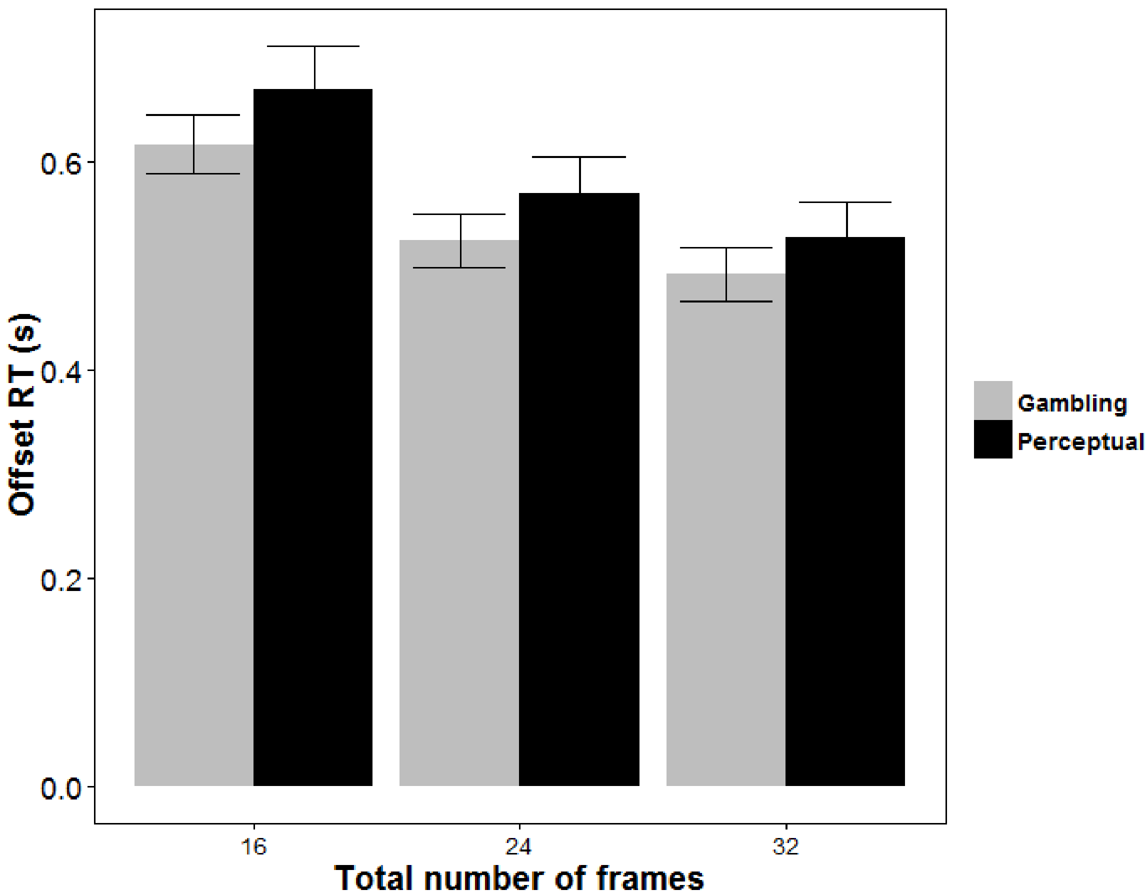

Figure 13. Choice RTs in Study 2.

Offset RTs, the duration between stimuli offset and the time of response, are conditioned by the total number of frames displayed and task (panels).

To do so, I calculated the time between stimulus offset and the response time (offset RT) and ran a hierarchical general linear model with the speed to respond (1/Offset RT) as the predictor, with the total number of dot samples (16, 24 or 32 frames) and task frame (perceptual coded as 1, gambling as 0) as fixed factors, and subjects as random factors. Participants made their choices faster when more samples of the stimulus were displayed (b = 0. 0289, $p < 0.001$). This is consistent with and is explained by previous findings in temporal preparation that demonstrate increased processing readiness during longer foreperiods, as people are better able to predict when the stimulus stream is likely to end as time passes (Schröter, Birngruber, Bratzke, Miller, & Ulrich, 2014). Participants did not have significantly different speeds between the two task frames (b = -0. 0347, $p = 0.771$).

Choice formation. To investigate the experimental manipulations on choice, I plot the group level estimates of the Bayesian hierarchical model of the psychometric function conditioned on task frame and gaze duration as illustrated in Figure 14. Choice was the proportion of choosing the first option, relative option attractiveness was the difference in mean number of dots between the two options, and gaze duration was measured by the relative duration of the first option as a proportion of the total duration across both options.

Indeed, relative gaze duration was found to impact choice. The fitted psychometric curves were shifted to the left in Figure 14 as the stimulus presentation duration of the first option increased, supporting the idea that people are biased to choose the option they look at the longest. The lateral shift between the curves may be quantified by the difference in the PSEs across two curves. Figure 15 depicts this difference between adjacent curves, and indicates that the shift is significant between all levels of relative duration.

The slope was unaffected by relative duration, and rather surprisingly; there were no differences across the gambling and perceptual task frames in any of the estimated parameters. This lack of difference is inconsistent with the finding in the first study that people were less biased in the perceptual task frame. Instead, this highlights that people may be particularly susceptible to biases when they are unable to control the information search process.

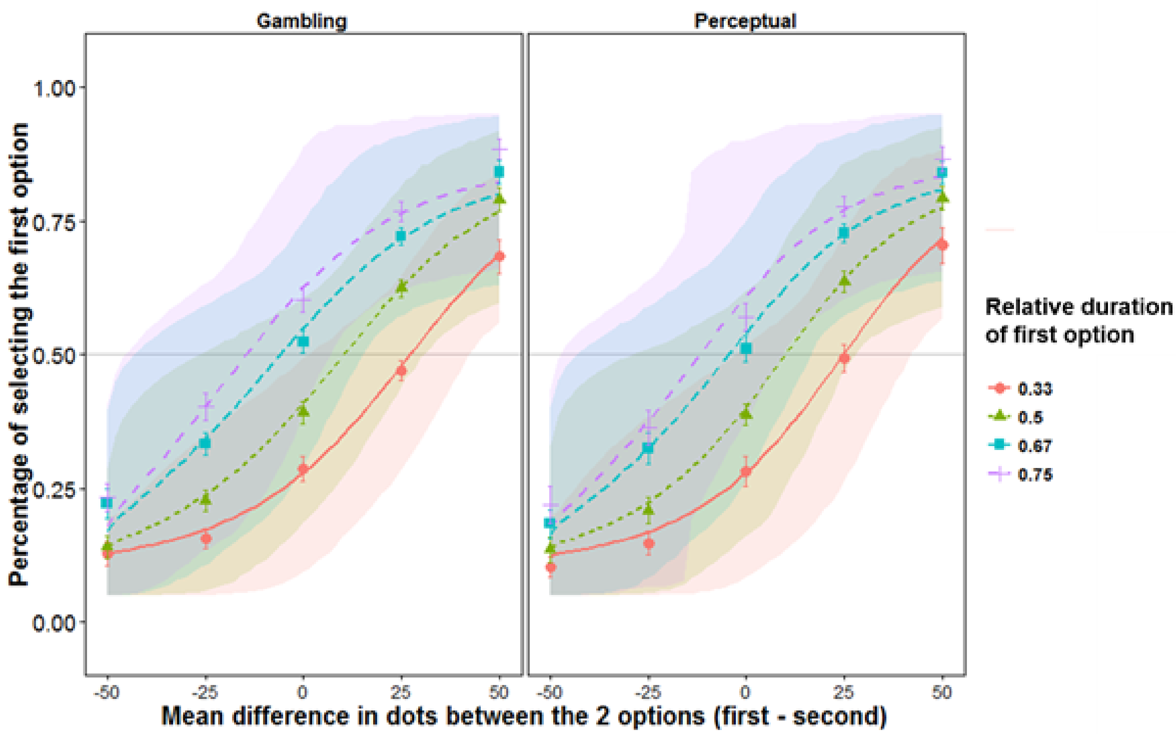

Figure 14. Psychometric curves in Study 2.

Data and corresponding psychometric curve describing the probability of choosing the first option against the difference in option attractiveness in Study 2. The data was conditioned by the relative duration of the first option (line colors and shape) and the task frame (vertical panels). The error regions indicate the 95% HDI of the fitted model, and the error bars indicate the average within-subject standard errors.

Finally, it is worth noting that the curves were shifted to the left, for example, the PSE was clearly positive and not zero when participants saw both options for an equal amount of time in the 50% relative gaze condition (green line in Figure 15). The lateral shift in PSE means that people require more dots in the first option for them to choose it, and suggests that people might have an overall preference to pick the second option over the first. There was no difference in PSEs between the perceptual and gambling conditions.

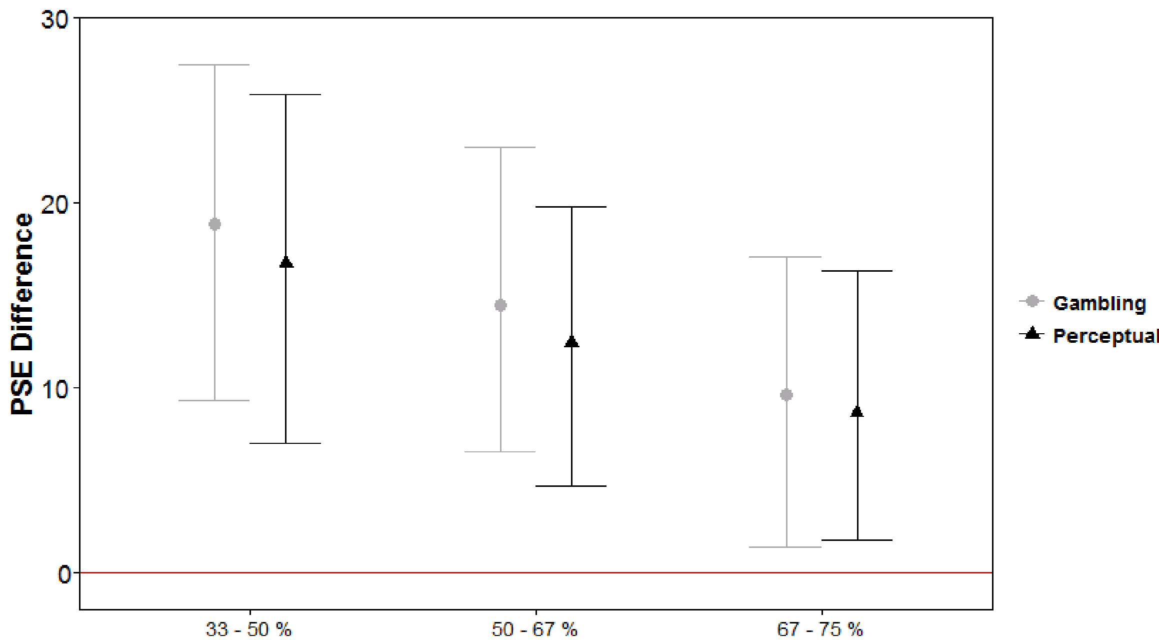

Figure 15. Point of subjective equality (PSE) contrasts.

This plots the difference between adjacent curves (difference between the levels relative duration). The PSEs were different across the levels of relative gaze duration, but not across the perceptual vs gambling task frames.

Model description and hypotheses. What is the underlying process that leads to the shift in PSE? To further investigate this, participants' choice and reaction time data were fit to the interrogation version of the classical drift diffusion model. This model is similar to the classical model outlined in the first study; however, instead of assuming that participants accumulate evidence up till they reach a threshold, the model assumes time-based stopping criteria which are more consistent with this study. Specifically, it assumes that participants accumulate information up till the time when the two dot stimuli disappear. At this point, participants choose the most favored option based on the information collected up till that time. Hence, only four parameters are estimated (no threshold):

- Bias β, the initial propensity to choose the first option, ranging from (-7 to 7, where 0 is the neutral point, a positive value means a bias toward choosing the first option, and a negative values means a bias toward choosing the second option).
- Non-decision time τ, ranging from 0.50 s to 1.0s.
- Baseline drift rate, the rate at which evidence accumulates in favor of the first relative to second option over time when both options equally attractive, which ranges from -3 to 3; and
- Drift sensitivity, the rate of increase in drift rate per level of attractiveness in the first option, ranging from -6 to 6.

I ran a hierarchical Bayesian interrogation model with group-level and subjective level parameter estimates. The parameters were allowed to vary across the two task frames and the four levels of relative duration. The attention model was also fitted (DIC: 63764; details in Appendix D) and compared with this classical model, and was found to have a poorer fit than this classical model (DIC: 62693).

The PSE could be manifested from two processes: an increase in the baseline drift rate of evidence accumulation with longer relative gaze durations, or a simple shift in bias toward the option as relative gaze duration increased. Both of these explanations are consistent with the modeling findings in the first study, which showed evidence of the drift rate changing in the gaze bias parameter and the initial bias across cueing conditions.

In this study, the value of the baseline drift must take into consideration that participants are assumed to pay full attention to the single option presented onscreen. As a result, the estimated drift values could increase with relative gaze, especially in the gambling condition. To elaborate, if participants have a gaze bias, information from the option they currently view will have a greater contribution to how the option is valued. So if the first option was presented 75% of the time, participants are likely to disproportionately weight the evidence of the first alternative, which results in a drift rate that is higher in the option viewed for the longest duration.

How a direct manipulation of stimulus exposure affects the start bias is more of an open question. While the location of an initial, peripheral cue was found to bias the starting point of evidence accumulation in the first study, varying stimulus viewing time is a fairly different manipulation that may not results in similar consequences.

Moreover, based on findings from the first study, I also expected to see greater drift sensitivity, the ability to discriminate the attractiveness of the two options, in the perceptual compared to the gambling condition and a constant threshold, the quantity of information accumulated, across all conditions.

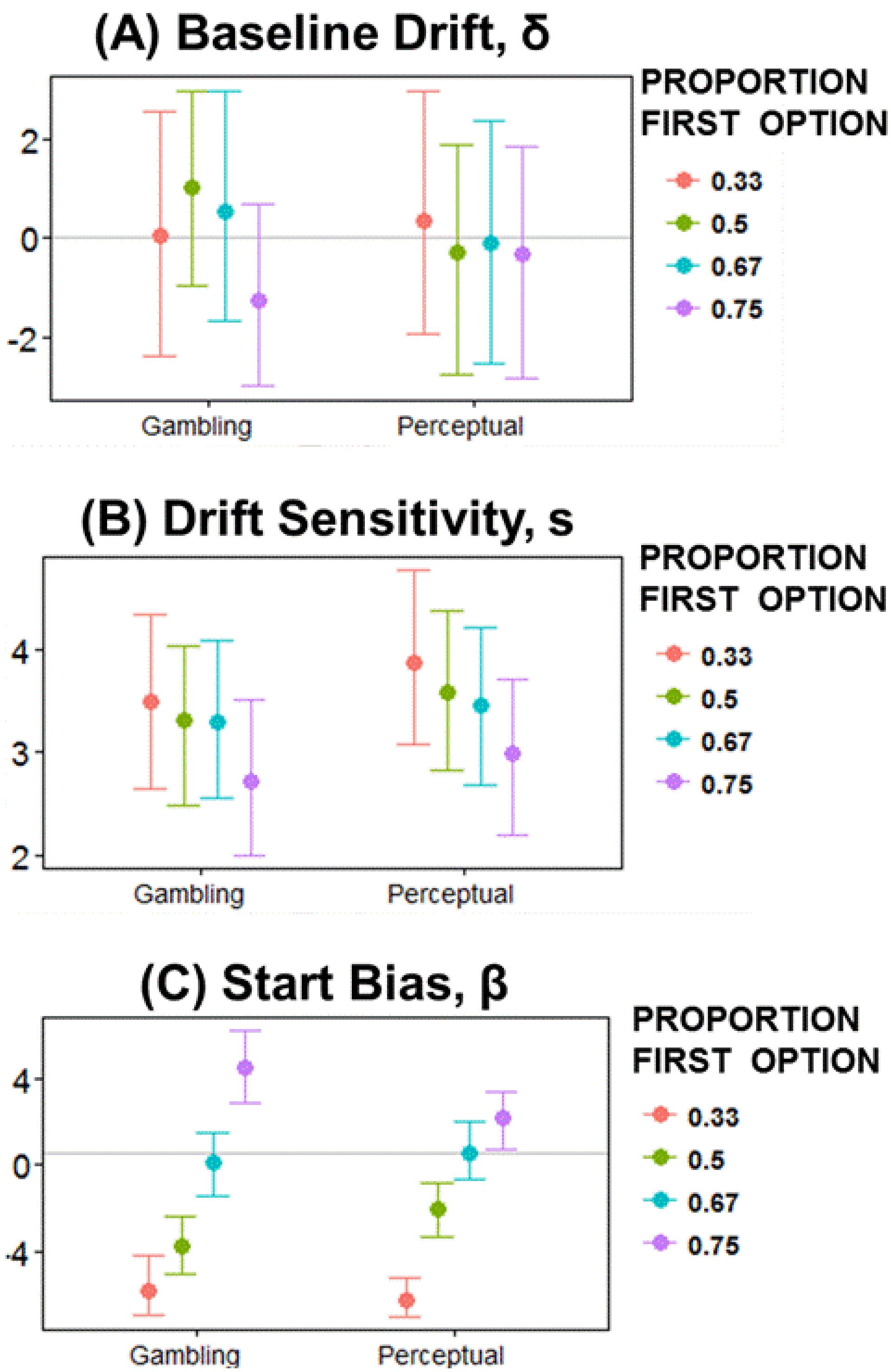

Figure 16. Parameter estimates of the classical drift diffusion model for Study 2.

Modeling results. The group-level estimates of baseline drift, drift sensitivity, and starting bias are presented in Figure 16. Mean non-decision time was estimated to be 0.0519s (HDI_{LOW} = 0.500 s and HDI_{HIGH} = 0.0553 s). Unlike the first study, the baseline drift rate, which describes the rate of evidence accumulation toward the first option when both options are equally attractive, remained no different from zero across all the relative gaze proportion and task conditions (Figure 16A). Likewise, drift sensitivity did not credibly differ across any of the manipulated conditions (Figure 16B), although there did seem to be a slight trend to be lower as the gaze proportion increased.

Drift sensitivity was overall positive, for both the gambling (Mean = 3.20, HDI_{LOW} = 2.24 and HDI_{HIGH} = 4.20) and perceptual (Mean = 3.47, HDI_{LOW} = 2.44 and HDI_{HIGH} = 4.46) conditions.

One particular condition of note, however, is when the relative duration was 75%. This was the only condition where the baseline drift and the drift sensitive seemed to be particularly low. Whether this condition is special or if this merely occurred by chance is up for speculation.

Unlike drift parameters which were relatively similar, the starting bias was found to increase as the relative proportion of exposure to the first option increased (Figure 16C). This is illustrated by the pairwise comparisons across the levels of relative exposure duration in Figure 17, which are mostly credibly different from zero. Surprisingly, participants were found to be generally biased away from the first option, with 50% gambling (Mean = -3.78, HDI_{LOW} = -5.09 and HDI_{HIGH} = -2.40) and perceptual (Mean = -2.03, HDI_{LOW} = -3.36and HDI_{HIGH} = -0.83) conditions being credibly below zero. Instead, it was the level above, the 67% gambling (Mean = 0.08, HDI_{LOW} =-1.42 and HDI_{HIGH} = -1.50) and perceptual (Mean = 0.54, HDI_{LOW} = -0.66 and HDI_{HIGH} =1.95) conditions, which were right at zero. These lower than expected bias values are consistent with the PSE fits and imply that people might tend to favor later rather than earlier options.

Moreover, pairwise comparisons across task type suggest that effect of relative gaze duration was higher in the gambling compared to the perceptual frame. While the bias across both tasks was at zero in the 67%, the bias value for the 75% was higher in the gambling than the perceptual frame, but in the 50% condition (Mean difference = 2.38, HDI_{LOW} =0.24 and HDI_{HIGH} = 4.39)., and was also lower in the gambling than the perceptual frame (Mean difference = -1.76, HDI_{LOW} = -3.49 and HDI_{HIGH} =0.24).

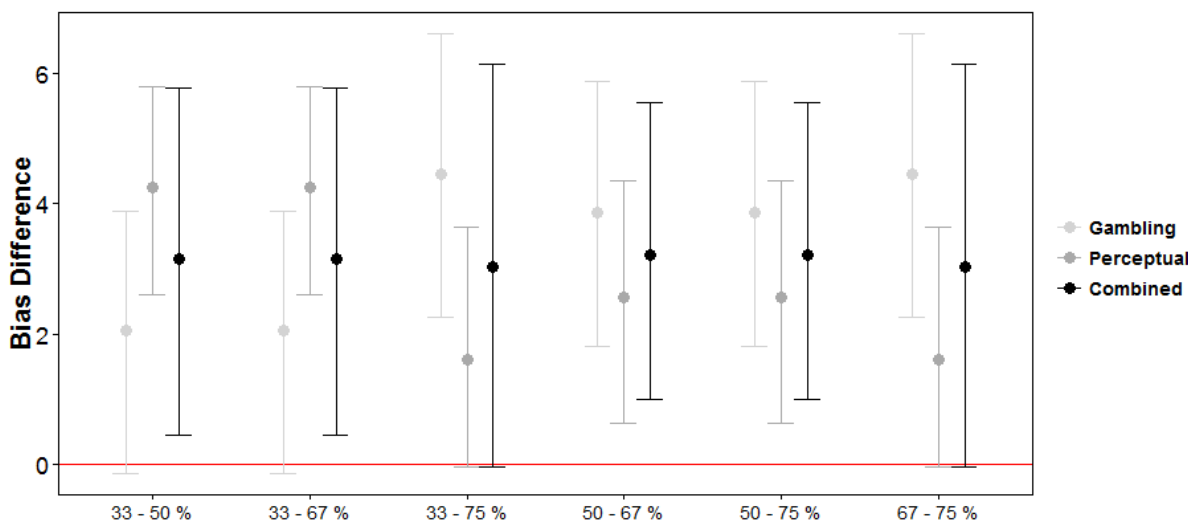

Figure 17. Bias contrasts in Study 2.

Discussion

The purpose of this second study was twofold: (1) To examine the robustness of the gaze bias under a more controlled environment, specifically, when exposure duration was directly manipulated and when the stimuli were presented centrally in an alternating sequence; and (2) to investigate the difference between actively engaging in information search in the first study compared to passively observing a stream of stimulus relevant information in the second study. In light of this, the findings were consistent with, but not identical to that of the first study. Firstly, perceptual and preference participants were equally susceptible the effect of manipulating the relative proportion of stimulus exposure, as shown by the shift in the PSE in the empirical results and the initial bias in the modeling results. The fact that people were influenced by the stimulus exposure duration in spite of the central stimulus location, attests to the strength of the phenomenon, even when no lateral saccades were required.

However, as mentioned, there were no differences between the perceptual and gambling frames, both in the empirical and modeling results. This means that the subjective value accumulated in the preference tasks may be considered as interchangeable with the sensory evidence accumulated in the perceptual task. That is, both tasks seem to share the same underlying evidence currency when participants were no longer able to voluntarily allocate relative attention across the two choice options.

This lack of difference may be contrasted with findings from the first study, which demonstrated that people were more likely to choose the item they viewed the longest in the gambling but not in the perceptual frame. Instead of affecting the information valuation process, the direct gaze manipulation appears to translate into an overall predisposition to favor the item with the greatest stimulus exposure duration. In other words, looking simply induces liking without actually affecting the mechanics of information valuation. I will elaborate on these differences between the studies in the general discussion section.

Moreover, the baseline drift rate and the drift sensitivity parameters did not vary across any of the conditions. The drift sensitivity also had the slight, overall non-credible, trend of being lower as the viewing duration became more disproportionate, especially in the 75% relative proportion condition. This suggests that people might value each piece of information less in the option they viewed for a relatively longer time, and could be because the relative exposure duration manipulation was fairly obvious to participants. In turn, the more salient proportion could have led participants to be more cautious of simply picking the one that seemed most prominent to them.

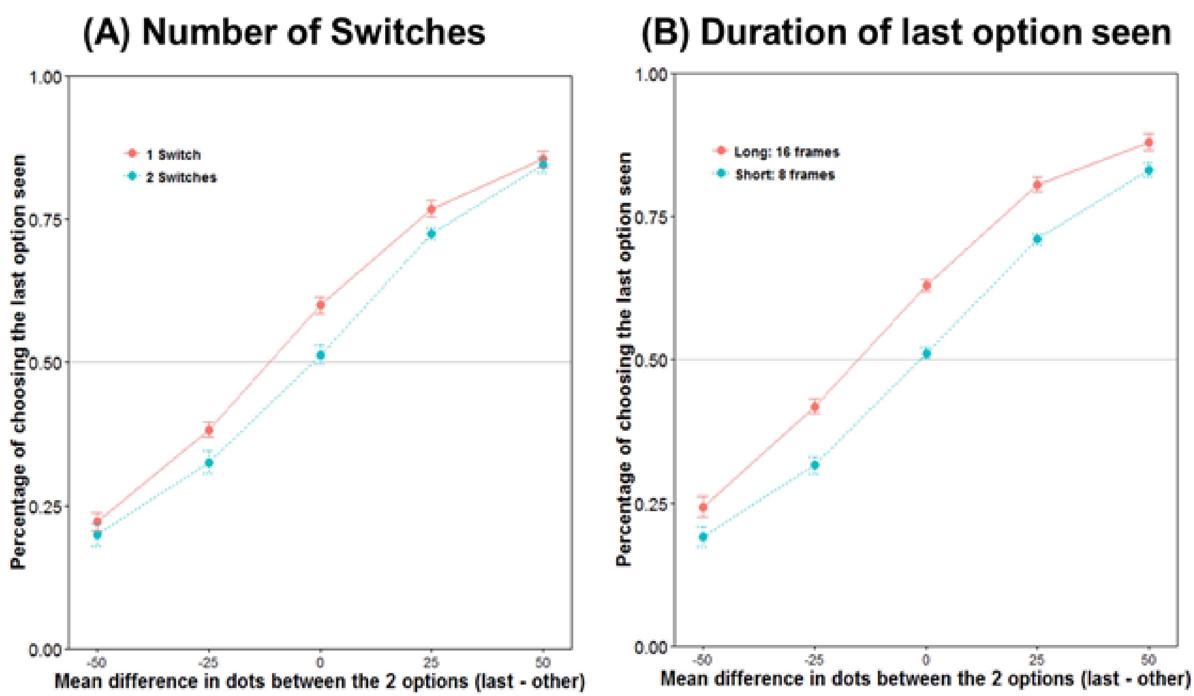

Figure 18. Psychometric function based on last option in Study 2.

This describes the probability of choosing the last option against the difference in option attractiveness in Study 2. The data was conditioned by (A) the number of frames in the last option viewed, and (B) the number of switches made, where 1 switch indicates the last option was the second option seen, and 2 switches indicates that the last option was also the first option presented twice. Note that the curves in the 1 switch and the long (18) frame conditions are shifted vertically upward.

Such a phenomenon is supported by the examining choice data conditioned on the number of switches made across the options. Figure 18A shows the percentage of choosing the last option seen, where 1 switch indicates that the last option was the second option seen, and 2 switches means that the last option was also the first option presented twice. The double presentation of an option in the 2 switch condition makes that option particularly salient to participants. As a result, this could have promoted discerning participants to be suspicious and more careful about picking the most “obvious” option. Thus, the option presented twice was associated with a decreased likelihood of choice, especially when the difference in attractiveness between options was less discriminable. This explanation is somewhat akin to how consumers are known to reject products that in advertisements that explicitly tell them what to buy or how to behave because they find these sort of marketing campaigns overly pushy (Bhattacharjee, Berger, & Menon, 2014), and highlights the significance of the perception of autonomy in choice.

Consider this with respect to the condition where participants only made a single switch. In this case, participants were more likely to choose the second option, which was the last thing they saw (red line in Figure 18A). The finding that participants tended to pick the last option they viewed lends indirect support to the finding in the first study that people have an inclination to look at the option they eventually pick just before choice, particularly when the extent of stimulus exposure is perceived to be equal when both options were presented once. The preference for the last option seen is further strengthened when the last option is presented for a longer duration (red line in Figure 18B). This goes against research proposing that people have an implicit preference for the first option they encounter (Carney & Banaji, 2012), and instead, implies that the option currently viewed and attended to is likely to contribute more evidence to the choice formation process.

Taken together, these results suggest that externally controlling stimulus presentation such that participants' passively observe information rather than actively and voluntarily seeking out relevant information leads to little differences across task frames. The study also illustrates the negative consequence of passive information uptake: people become much more susceptible to external, extraneous biases once they are no longer actively engaged in information search process.

CHAPTER 5: GENERAL DISCUSSION

Although there has been some discussion on the differences between perceptual and preference choice (Shadlen, Kiani, Hanks, & Churchland, 2008; Summerfield & Tsetsos, 2012), there has been relatively little progress on this front because of the methodological hurdles involved in equating the two paradigms in an empirical experiment. Hence, this dissertation makes the novel contribution of directly comparing the process of choice formation across preference and perceptual tasks in an empirical experiment.

Summary of the Studies

The first study took on a more exploratory approach in order to characterize how people naturally search for and value information. Results demonstrate that different higher-order task goals motivate people to adjust their search strategy in terms of the relative and total quantity of information they gather. To elaborate, participants obtained more information in the perceptual condition when it was difficult to discriminate between the attractiveness of the two options. In general, they also shift toward looking at the more favored option just before choice. However, this gaze bias was reduced in the perceptual frame, as perceptual participants maintained good discrimination accuracy even when they acquired less information. Data from both tasks were well described by a diffusion model of evidence accumulation which values and integrates stimulus information based on eye gaze location. Consistent with behavioral results, the modeling reveals that distinction between task goals lies in quantitative differences across cognitive parameters: perceptual choice was associated with a lower gaze bias and greater information valuation than preferential choice.

To test the role of active and voluntary engagement in the information search process, I ran a second study where participants passively viewed a stream of information samples and directly manipulated stimulus exposure duration to the information samples in each option. The results only partially replicate the first study: perceptual and preference participants were equally affected by the relative stimulus exposure duration manipulation as they had the tendency to pick the item presented for the longer duration. Thus, in contrast to the first study, participants in the perception condition in the second study were found to be just as susceptible to the gaze bias when they could not control the relative acquisition of information between choice options.

Table 3. Comparison of the first and second studies

	First study	Second study
Voluntary Control	• Free viewing paradigm • Active information search • Optional stopping	• Fixed viewing (on central point) • Passive information viewing • Interrogation stopping rule
Relative gaze	• Options presented at the same time • Relative attention between options • Fixation duration measured at each location over the entire trial	• Options presented sequentially • Full attention at each time point • Stimulus exposure duration manipulated over the entire trial
Results	• Perceptual choice is associated with greater valuation and a lower gaze bias than preferential choice • Gaze bias reflected in valuation: information from fixated item is discounted.	• Perceptual and preferential choices were equally affected by relative gaze duration. • Gaze bias reflected in the initial bias rather than in the information valuation process

Passive vs Active Task Engagement

Why were participants in the perceptual condition in the study unable to better modulate their gaze biases? The answer probably lies in the difference in how the options were presented across the two experiments (Table 3). Recall that in the first study, both options were displayed at the same time so participants had to form a strategy about how best to acquire information from the options. As a result, participants were forced to divide their attention at each moment as they had to pick which option to allocate their attention to, or, in some cases, decide if they would rather attempt to attend to both options at the same time.

Conversely, in the second study, participants passively viewed the options which were presented in an alternating sequence. This meant that stimulus exposure, and in consequence, gaze duration was relative at the aggregate level across the entire trial duration but not at the momentary time-by-time level. Moreover, it was much easier for participants to simply sit back and observe the single stream of information available as they did not have to actively select what information to attend to.

These distinctions highlight the importance of being actively engaged in the intermediate steps necessary to achieve a higher-order goal, which channels a broad set of research concerned with how active exploration of the environment affects behavior, from the previously mentioned field of embodied cognition (Anderson, 2003; Wilson, 2002), to more applied work in educational research. In the latter, researchers have long debated the merits of using a teaching style that emphasizes active student involvement compared to passive observation in the classroom, with the growing consensus that students tend to do better when more interactive instructional techniques are used over the traditional didactic style of using lectures to disseminate information. For example, subjective reports and objective assessments of students performance improved when they engaged in role playing simulations (DeNeve & Heppner, 1997), prepared and selected course-relevant questions in a Jeopardy game (Benek-Rivera & Mathews, 2004), or learned object structures by actively rotating the objects in virtual reality (James et al., 2002).

Cognitive Dissonance Theory (Festinger, 1957) lends further credence to the idea that active engagement in a task leads to a higher likelihood of viewing it in a positive light due to effort justification. More specifically, the process of being actively engaged in searching for information is highly effortful, suggesting that participants in the first study may attribute greater value to the decision task in the attempt to justify the work they put into the process of searching for information. Furthermore, according to Cognitive Evaluation Theory (Benware & Deci, 1984; Ryan & Deci, 2000), people need to have a sense of autonomy, that is, have an internal perceived locus of causality, in order to develop of intrinsic motivation toward a task. The significance of autonomy as compared to control in maintaining of intrinsic motivation is also supported by research in education, as teachers that support autonomy in the classroom as opposed to being controlling are found to inspire greater intrinsic motivation and curiosity in student learning (Ryan & Grolnick, 1986). Moreover, extensive control in the classroom is associated with loss of initiative and poorer learning in complex, problem solving tasks (Benware & Deci, 1984; Grolnick & Ryan, 1987).

The findings across the two studies may be interpreted in the context of how active, autonomous learning relates to intrinsic motivation. The side-by-side placement of the two dynamically updating options in the first study forced participants to make a conscious, voluntary effort to acquire information in order to achieve a higher-level goal. In doing so, participants had to actively engage in goal-directed behavior, which was driven by the perceptual or preferential framing instructions they received. Such active engagement is likely to foster a higher level of intrinsic motivation in participants, which could spur them to develop decision strategies that maximize the probability of choosing the option with the most dots on average (perceptual goal) or the highest subjective utility (in the preference goal). Consequently, these two higher-level goals could have led to a large divergence in information search strategies, valuation, and subsequent patterns of choice behavior across the two framing conditions.

In contrast, participants in the second study did not need to put in any effort to divide their attention and actively search for information. Instead, they simply had to fixate in the center of the screen and observe the stream of incoming information that appeared. Naturally, the less demanding but more controlling task was more likely to make participants in the second study feel comparatively less motivated than participants in the first study as they were stripped of their autonomy to engage the information search process. As the search process from the crux of how participants regulate behavior to meet their goal, it is not surprising that eliminating the voluntary search process in the second study effectively cancelled out the distinctive aspects of choice formation that differentiate the original intent to focus on perception or preference. As a result, participants across both frames behaved similarly and were equally affected by the relative gaze manipulation.

It is possible to quantitatively test this explanation by equating the two experiments and comparing the difference in PSE of the psychometric curves across two conditions of gaze proportion. To do so, I obtained the ratio of looking at the right vs left option for every trial in the first study, and then subsequently binned the ratios into 3 conditions that indicate the percentage of looking at the right relative to the left option: below 33%, 33 to 66% or above 66% looking right. As participants only saw each option in the study once or twice in the second study, I determined the PSEs curves in these three conditions when participants made two saccades, and calculated the contrast between the below 33% and above 66% conditions. These contrasts were then compared to the contrast of the 33% and 66% gaze proportions (of looking at the first relative to the second option) in Figure 19.

The results of the comparison are as expected. The difference in PSEs across the two gaze duration conditions in both the gambling (*M* = 33.3 dots) and perceptual (*M* = 29.0 dots) task frames are similarly high and comparable to that of that of the gambling condition (*M* = 35.1 dots) in the first study. The red line in the figure indicates the average across these three conditions (32. 5 dots), and may be contrasted with the lower PSE in the perceptual frame in the first study (*M* = 18.8 dots). This supports the idea that participants in the perceptual condition in the second study were more affected by the gaze bias than in the first study when they passively viewed the stimulus stream.

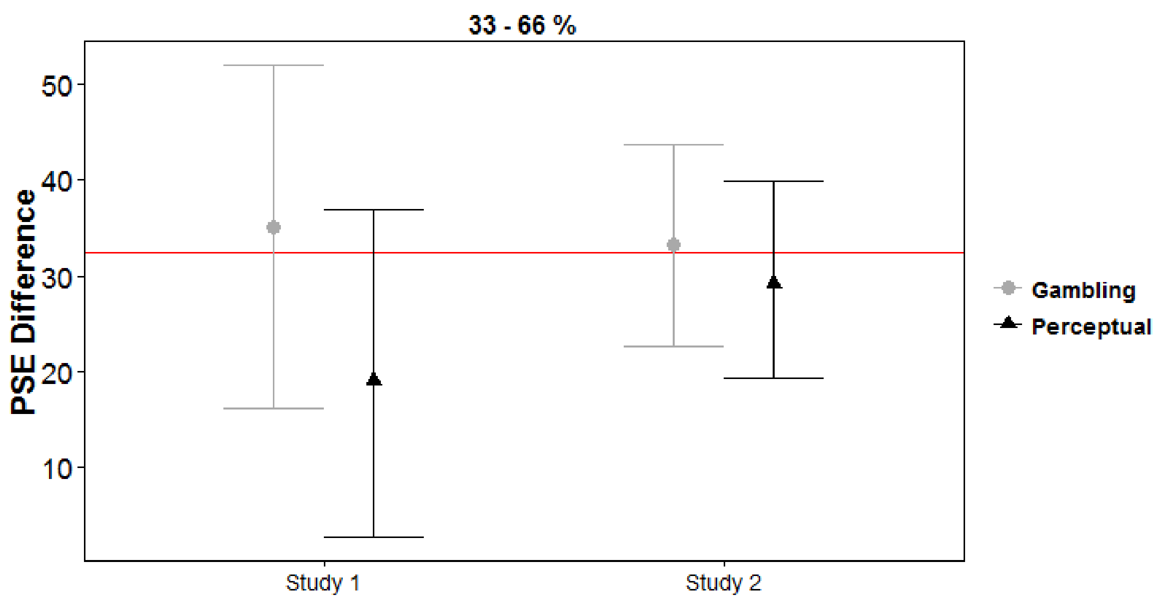

Figure 19. Comparing the PSE difference across the two studies.

Such an explanation gels with previous work that investigated how people choose between a certain versus an uncertain option using the original version of the Flash paradigm (Zeigenfuse et al., 2014). Although the main setup and framing instructions are similar to the two studies presented here, the original paradigm had slightly different stimuli: the certain option consisted of static display with a fixed number of dots that remained onscreen throughout the entire trial, while the number and location of dots in uncertain option was dynamically updated every 50 ms from an underlying reward distribution on the other side of the screen at the same time. One of the main empirical findings was that participants consistently expressed the desire to choose the uncertain option over the certain option when the task was framed as a gambling rather than a perceptual task because participants tended to weigh the evidence sampled from the uncertain option more optimistically in the gambling frame.

This dissertation sheds light on the study's findings. The static versus dynamic nature of the two options means that it is more beneficial for participants to attend to the dynamically updating uncertain option for a relatively longer duration, because all the information they can gather from the static fixed option may be obtained from a single quick glance. Thus, by encouraging a disproportionate viewing strategy, the task setup indirectly lays the foundation for the gaze bias, which induces participants to pick the uncertain option – the option they were likely to have looked at for a greater period of time. Moreover, the relatively more active and effortful process of eliciting information from the uncertain option compared to the quick and easy process in the static, certain option, further contributes to the inclination to favor the uncertain option.

Methodological Advances and Extensions

Using eye-tracking to uncover the choice processes in Flash Fishing paradigm extends existing research methodology in decision making along two fronts: as a new, rapid way of investigating experienced based decision making, and as comprehensive process tracing approach to uncover moment-by-moment information search processes.

The Flash Fishing paradigm itself is novel in that it builds on typical experience-based paradigms where people deliberately sample information from choice alternatives in a slow and controlled manner over an extended set of trials (Hertwig & Erev, 2009), and is also different from decisions from description paradigms that focus on static, symbolic descriptions of stimuli (Weber et al., 2004) which explicitly state the payoffs and probabilities of each choice alternative. What is interesting about the dynamic nature of the stimuli is that the rate of updating may be sped up to approximate decisions-from-description as participants can quickly grasp the entire decision space, or slowed down to be more comparable to decisions-from-experience paradigms.

Additionally, this study is an example of using eye-tracking as a process-tracing technique, a method of tracking behavior over time so as to draw inferences about the current state of information accumulation in decision making. While eye-tracking is more commonly used as a passive measure of revealing a participants' current state of preference, the dynamic stimuli present in the Flash Fishing paradigm channels more recent work by opening a window into the active process of information search strategies (Franco-Watkins & Johnson, 2011; Lohse & Johnson, 1996; Pachur, Hertwig, Gigerenzer, & Brandstatter, 2013; Schulte-Mecklenbeck, Kuehberger, & Ranyard, 2010) as eye gaze reflects how participants voluntarily seek out information from the environment rather than simply reflect the existing levels of attraction toward the options.

Although similar analyses have been used in previous eye-tracking studies of preferential decision-making, the studies have always made the implicit assumption that people only attend to a single fixated item. This leads to the analyses of either incomplete or imprecise eye fixation data: the fixations on regions outside the choice options are excluded (Shimojo et al., 2003), or the fixations are categorized in a binary fashion depending on whether they fall on the left or right of the screen (Isham & Geng, 2013; Krajbich et al., 2010). Contrary to this, the eye tracking data show that people not only look directly at the options, but also attempt to attend to both options at the same time by looking in the center. Recall that transition probabilities suggest the most common approach to information search occurs by looking at the center, before looking towards the more attractive option in the second saccade. This pattern demonstrates people can effectively attend to the information present in both options at the same time when they look at the center.

Hence, this paradigm calls for a more nuanced approach to classifying patterns of eye gaze. Although I did not investigate this extensively because this was not the main purpose of the study, a cursory analysis of the transition probabilities across saccades reveal variability in participants' preferred eye gaze patterns: apart from the above mentioned strategy of looking first at the center and then to the more attractive option, some people prefer to keep their eyes on the center through the entirety of the trial, while others systematically alternate looking between the left and right options immediately from the first saccade.

These findings are promising, and illustrate how tracking eye movements in the Flash Fishing may reveal individual differences in how people attend to information in a choice set. Given that the frequency in which people oscillate between sampling from the different options (in a piecemeal versus a more comprehensive fashion) has been shown to impact choice (Hills & Hertwig, 2010), a natural line of future research would be to explore how eye tracking data reflects different types of information search strategies using this paradigm.

Gaze, Information Quantity, and Attention: Are they All the Same?

Overall, this dissertation has cast a wide net in order to make comparisons across several distinct approaches of studying decision making. One challenging aspect in this endeavor is the need to maintain sufficient leeway and generalizability between shared constructs and measures, while keeping the more subtle details of each approach intact. Take for instance, the main phenomenon of interest, the gaze bias. Results from both studies provide evidence in support of a gaze bias in which choice appears to favor the item looked at for a relatively longer time. To express this succinctly: looking equates to liking. Yet what lies beneath this general empirical finding? Or more specifically, what exactly constitutes looking? This is a critical question that will clarify the underlying cause of the gaze bias.

The empirical experiments refer to looking in three different ways:

- In the first study, looking is conceptualized as divided, voluntary and overt attention to the two competing options onscreen, in line with research in preferential decision making, and is operationalized in terms of moment-to-moment relative gaze proportions.
- In the second study, the sequential alternating option display means that looking may be construed as a form of overt attention, but not divided and voluntary attention. It is also operationalized in terms of relative gaze proportion aggregated across the entirety of each trial.
- Across both studies, the uptake of visual information presupposes looking, so looking duration is also monotonically related to, and may be considered inter-changeable with, the quantity of information acquired in the search process.

On the other hand, cognitive modeling reveals two components of the gaze bias:

(1) A tendency to discount contributions from the unfixated option in the evidence accumulation process as manifested by the fixation weighting parameter θ, in the first study, and

(2) A general predisposition to simply choose the item that is viewed for a relatively longer duration, as manifested by the initial bias β, in the first and second study.

As the first component of the gaze bias concerns how relative attention is split among the two options at each time point, it is most likely linked to voluntary divided attention. The finding that voluntary, divided attention is required for perceptual participants to mitigate effect of the gaze bias in the first study, but does not interfere with the overall increase in choosing the option with a longer exposure duration in the second study, supports the notion that voluntary, divided attention is indeed associated with the first but not the second component of the gaze bias.

Consequently, the second component of the gaze bias may actually be driven by overt attention or information quantity, that is, people could have a predisposition to choose the option that they view for a longer time, or to choose the option they have more information about.

I sought to test these two explanations against each other. My first inclination was to manipulate gaze duration while fixing the number of samples, which effectively changes the speed in which information is presented (e.g. presenting 8 frames of option 1 at 20 Hz and then presenting another 8 frames of option 2 at 40 Hz would mean that option 1 is presented for 67% of the overall duration but the quantity of information across options is kept the same). However, pilot testing revealed that sequentially presenting two options that updated at different speeds led to a very jarring and unnatural viewing experience. Hence, I did not control for this difference in information quantity in this study, but ran an additional short experiment where stimulus exposure duration and information quantity were manipulated in by repeating a sequence of unique samples in certain conditions (Table 4 in Appendix E).

For example, a condition where the first option had 8 unique samples and the second had 16 unique samples would be compared with another condition where the first option had 8 unique samples and the second had 8 unique samples presented twice for a total of 16 samples. As such, the gaze proportion was equal (33% for the first option) in both these conditions, but the former condition carried additional unique information. The results replicate that of the second study: participants were more likely to choose the option presented for an overall longer duration, but the extent to which the samples carried unique information did not matter.

Although this is not the most rigorous test of information quality, it supports the idea that it is the act of overly attending to an option, rather than the actual discrete quantities of unique information contained in the option, that is associated with the second component of gaze bias. This proposal that increasing overt attention leads to the general predisposition toward liking the option corroborates with the mere exposure effect, where repeated, unreinforced exposure to a stimulus can enhance participants' attitude towards it (Bornstein & D'Agostino, 1992; Zajonc, 1968, 2001).

Thus, to summarize, the gaze bias may be qualitatively and quantitatively characterized at two levels: the disproportionate weighting of the fixated compared to the unfixated choice options resulting from having to voluntarily divide attention at each time point; and a simple shift toward liking the option looked at for a relatively longer duration in line with the mere exposure effect.

Conclusions

In conclusion, this dissertation has contributed to previous research by describing the process of choice formation over two empirical studies in several ways. Findings from both studies not only attest to the overall structural generalizability of the choice formation process across different higher-level task goals, but also illustrate how several more quantitative details are task specific.

People can effectively modulate their information search and valuation strategy by adjusting the relative and total quantity of information acquired in perceptual decision making, so as to fulfill the goal of objectively assessing sensory information. Participants in the perceptual frame were found to make more saccades in the perceptual rather than the preference frame when it was difficult to discriminate between the attractiveness of the two options, and to value the contribution of information from both fixated and unfixated items more equally than participants in the preference frame. As a result, perceptual participants were less susceptible to external biases, like the gaze bias, than preference participants, who were simply asked to choose the option they preferred.

However, participants need to be actively and voluntarily engaged in the information search stage before higher-order intentions are manifested in the choice outcome. When participants passively observe task-relevant information, the lack of autonomy in the choice formation process makes them incapable of overcoming biases even if they originally intended to be objective. Thus, participants in both the perceptual and gambling conditions were equally likely to be influenced by the gaze bias when they could not control how information was acquired. Together, these results highlight the importance of relative, voluntary, overt attention during the processes of information search and valuation across perceptual and preferential choice.

What does this all mean for Juliet? Recall that Juliet was pretty adamant about her intention to resist the pull of the gaze bias. Given that she has the power to decide where and when to look at Paris, Juliet seems to be in a strong position to keep her emotions in check. But what happens if Paris does not even appear, and instead, Romeo steps into view while she is passively waiting at the feast? Perhaps Juliet is not that infallible after all.

APPENDICES

APPENDIX A: Framing Manipulation

Study 1: Two options presented on the left and right

Preference condition.

1. This is a preference task: look at the two ponds and choose which pond you would rather fish from.
2. You will see 2 fishing ponds, each represented by a circular patch of dots onscreen. The dots represent the number and locations of fish that are on the surface of the pond at each moment. Every 50 ms, the number and locations of fish surfacing will be updated.
3. Your task is to choose the pond from which you would prefer to fish from. Press “1” to choose the left pond, and press “2” to choose the right pond. Once you make your pick, you will catch all the fish that surface in the next 50 ms in the pond you chose. After which, the ponds will disappear and you will see the number of fish you caught in this trial.
4. At the end of the experiment, we will pay you a bonus based on the total number of fish you have caught across trials. We expect the bonuses to range between $1 and $5.

Perceptual condition.

1. This is a perceptual task: look at the two ponds and choose the pond which has more fish surfacing on average.
2. You will see 2 fishing ponds, each represented by a circular patch of dots onscreen. The dots represent the number and locations of fish that are on the surface of the pond at each moment. Every 50 ms, the number and locations of fish surfacing will be updated.
3. Your task is to choose the pond that contains more fish on average. Press “1” to choose the left pond, and press “2” to choose the right pond. Once you make your pick, the ponds will

disappear and we will tell you how many fish that surface on average in the pond you chose. That number will be the number of fish you caught in this trial.

4. At the end of the experiment, we will pay you a bonus based on the total number of fish you have caught across trials. We expect the bonuses to range between $1 and $5.

Study 2: Two options (red and blue) presented centrally and sequentially

Preference condition.

1. This is a preference task: look at the two ponds and choose which pond you would rather fish from.
2. You will see 2 fishing ponds, each represented by a red or blue circular patch of dots onscreen. The dots represent the number and locations of fish that are on the surface of the pond at each moment. Every 50 ms, the number and locations of fish surfacing will be updated.
3. Your task is to choose the pond from which you would prefer to fish from. Press “1” to choose the RED pond, and press “2” to choose the BLUE pond. Make your choice after the ponds disappear. You will catch all the fish that surface in the next 50 ms in the pond you chose. After which, you will see the number of fish you caught in this trial.
4. At the end of the experiment, we will pay you a bonus based on the total number of fish you have caught across trials. We expect the bonuses to range between $1 and $5.

Perceptual condition.

1. This is a perceptual task: look at the two ponds and choose the pond which has more fish surfacing on average.

2. You will see 2 fishing ponds, each represented by a red or blue circular patch of dots onscreen. The dots represent the number and locations of fish that are on the surface of the pond at each moment. Every 50 ms, the number and locations of fish surfacing will be updated.
3. Your task is to choose the pond that contains more fish on average. Press “1” to choose the RED pond, and press “2” to choose the BLUE pond. Once you make your pick, we will tell you the number of fish that surface on average in the pond you chose. That number will be the number of fish you caught in this trial.
4. At the end of the experiment, we will pay you a bonus based on the total number of fish you have caught across trials. We expect the bonuses to range between $1 and $5.

APPENDIX B: The Hierarchical Bayesian Drift Diffusion Models

All the diffusion models were estimated using the rjags (Plummer, Stukalov, & Denwood, 2015) package with the JAGS Wiener module (Wabersich & Vandekerckhove, 2014), an extension for the Just-Another-Gibbs-Sampler (JAGS) in R. In all the models, Markov Chain Monte Carlo (MCMC) methods were used to generate 3 chains of 2000 steps estimated from the posterior distribution of each parameter.

The models were Bayesian hierarchical models with participant-level and group-level estimates. All of the parameters except non-decision time (single value only throughout all conditions) were allowed to vary across the conditions.

STUDY 1: CLASSICAL OPTIONAL STOPPING DRIFT DIFFUISION MODEL

```
model {
  for ( i in 1:Ntotal ) {
     y[i]~ dwiener(alpha[x1[i],x2[i],subj[i]],tau[subj[i]],beta[x1[i],x2[i],subj[i]],deltaEff[i])
     deltaEff[i]<- delta[x1[i],x2[i],subj[i]] + deltaScale[x1[i],x2[i],subj[i]]*(x3[i]-3)
  }

  for (s in 1 : Nsubj) {
    tau[s] ~ dnorm(muTau, tauTau) T( .1 , 1 )
    for ( j2 in 1 : Nx2Lvl ) {
      for ( j1 in 1 : Nx1Lvl ) {
        alpha[j1,j2,s] ~ dnorm(muAlpha[j1,j2],tauAlpha) T(.1,5)
        beta[j1,j2,s] ~ dnorm(muBeta[j1,j2],tauBeta) T(.1,.9)
        deltaScale[j1,j2,s] ~ dnorm( muDeltaScale[j1,j2] , tauDeltaScale )  T(-5 , 5)
        delta[j1,j2,s] ~ dnorm( muDelta[j1,j2] , tauDelta ) T( -2 , 2 )
   }}}

  tauTau ~ dgamma(.001, .001)
  muTau ~ dunif(.1, 1)

  for (jC2 in 1:Nx2Lvl){
    for (jC1 in 1:Nx1Lvl){
      muAlpha[jC1,jC2] ~ dunif(.1,5)
      muBeta[jC1,jC2] ~ dunif(.1,.9)
      muDeltaScale[jC1,jC2]  ~ dunif(-5,5)
      muDelta[jC1,jC2]  ~ dunif(-2,2)
  }}

  tauAlpha ~ dgamma(.001, .001)
  tauBeta ~ dgamma(.001, .001)
  tauDeltaScale ~ dgamma(.001, .001)
  tauDelta ~ dgamma(.001, .001)
}
```

STUDY 1: ATTENTION DRIFT DIFFUISON MODEL

```
model {
  for ( i in 1:Ntotal ) {
      y[i] ~ dwiener(alpha[x1[i],x2[i],subj[i]],tau[subj[i]], beta[x1[i],x2[i],subj[i]], delta[i])
      delta[i]<- deltaScale[x1[i],x2[i],subj[i]] * (
           pRight[i]*(vRight[i] - fixDiscount[x1[i],x2[i],subj[i]] * vLeft[i])
           + pCenter[i]*(vRight[i] - vLeft[i])
           + pLeft[i]*(fixDiscount[x1[i],x2[i],subj[i]]* vRight[i] - vLeft[i]))
  }
  for (s in 1 : Nsubj) {
    tau[s] ~ dnorm(muTau, tauTau) T( .1 , 1 )
    for ( j2 in 1 : Nx2Lvl ) {
      for ( j1 in 1 : Nx1Lvl ) {
        alpha[j1,j2,s] ~ dnorm(muAlpha[j1,j2],tauAlpha) T(.1,5)
        beta[j1,j2,s] ~ dnorm(muBeta[j1,j2],tauBeta) T(.1,.9)
        deltaScale[j1,j2,s] ~ dnorm( muDeltaScale[j1,j2] , tauDeltaScale )  T(-5,5)
        fixDiscount[j1,j2,s] ~ dnorm( muFixDiscount[j1,j2] , tauFixDiscount )  T(.1,.99)
  }}}
  tauTau ~ dgamma(.001, .001)
  muTau ~ dunif(.1, 1)

  for (jC2 in 1:Nx2Lvl){
    for (jC1 in 1:Nx1Lvl){
      muAlpha[jC1,jC2] ~ dunif(.1,5)
      muBeta[jC1,jC2] ~ dunif(.1,.9)
      muDeltaScale[jC1,jC2]  ~ dunif(-5,5)
      muFixDiscount[jC1,jC2]  ~ dunif(.1,.99)
  }}
  tauAlpha ~ dgamma(.001, .001)
  tauBeta ~ dgamma(.001, .001)
  tauDeltaScale ~ dgamma(.001, .001)
  tauFixDiscount ~ dgamma(.001, .001)
}
```

STUDY 2: CLASSICAL INTERROGATION DRIFT DIFFUISION MODEL

```
model {
  for ( i in 1:Ntotal ) {
    y[i] ~ dbern(mu[i])
    mu[i] <- pnorm(ev[i],0,sigma[i])
    sigma[i] <- (.1)^2 * (rt[i]-tau[subj[i]])
    ev[i] <- beta[x1[i],x2[i],subj[i]] + deltaEff[i] * (rt[i]-tau[subj[i]])
    deltaEff[i]<- delta[x1[i],x2[i],subj[i]] + deltaScale[x1[i],x2[i],subj[i]]*(x3[i]-3)
  }

  for (s in 1 : Nsubj) {
    tau[s] ~ dnorm(muTau, tauTau) T( .05 , 1 )
      for ( j2 in 1 : Nx2Lvl ) {
        for ( j1 in 1 : Nx1Lvl ) {
          beta[j1,j2,s] ~ dnorm(muBeta[j1,j2],tauBeta) T(-7,7)
          delta[j1,j2,s] ~ dnorm( muDelta[j1,j2] , tauDelta ) T(-3,3)
          deltaScale[j1,j2,s] ~ dnorm( muDeltaScale[j1,j2] , tauDeltaScale ) T(-6,6)
  }}}

  tauTau ~ dgamma(.001, .001)
  muTau ~ dunif(.05, 1)

  for (jC2 in 1:Nx2Lvl){
     for (jC1 in 1:Nx1Lvl){
        muBeta[jC1,jC2] ~ dunif(-7,7)
        muDelta[jC1,jC2]  ~ dunif(-3,3)
        muDeltaScale[jC1,jC2]  ~ dunif(-6,6)
  }}

  tauBeta ~ dgamma(.001, .001)
  tauDelta ~ dgamma(.001, .001)
  tauDeltaScale ~ dgamma(.001, .001)
}
```

APPENDIX C: Classical Drift Diffusion Model Parameter Estimates for Study 1

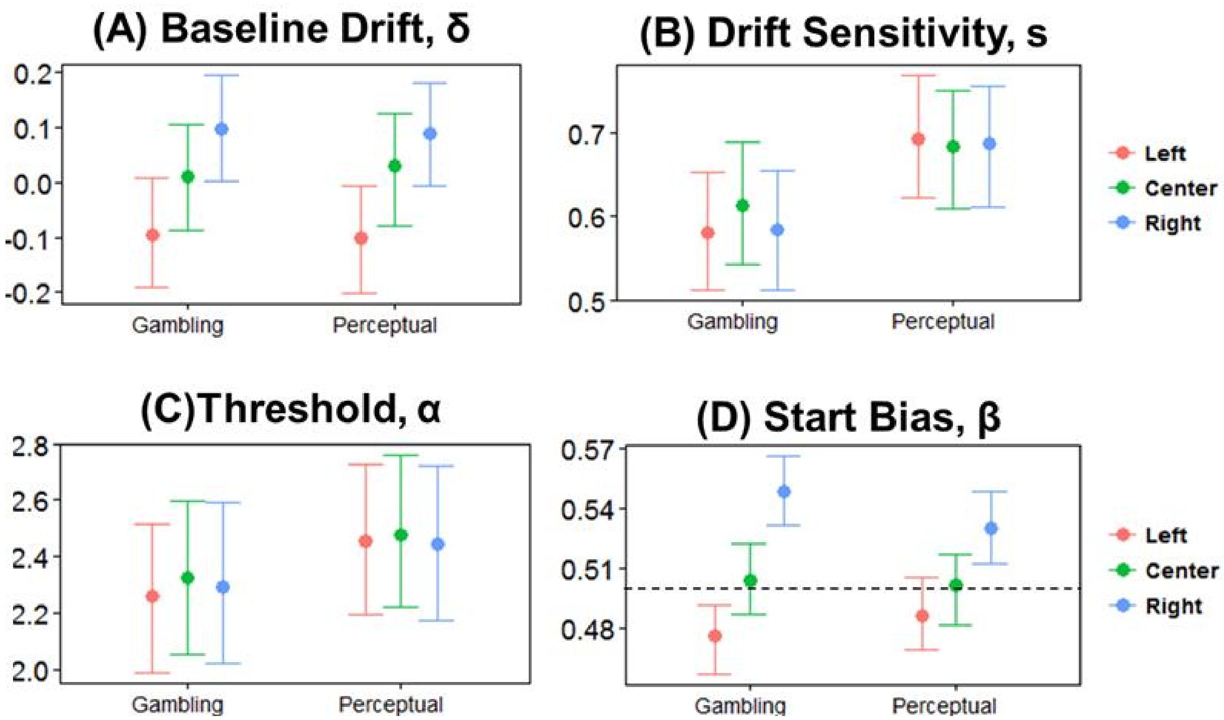

Figure 20. Parameter estimates of the classical drift diffusion model for Study 1.

In the classical drift diffusion model, the baseline drift rates (Figure 20A) across all the conditions were, as expected, close to zero. Although the mean drift rates for the cued conditions shifted slightly in line with the location of the cue, the shift was not significant. Likewise, the sensitivity of the drift rate to the difference in option attractiveness was significantly higher in the perceptual frame only for the left cue (Mean slope difference = 0.11, HDI_{LOW} = 0.004 and HDI_{HIGH} = 0.208) but not in the center or right cue condition (Figure 20B). As a result, there was no main effect of task frame on drift sensitivity. The thresholds were also similar across conditions (Figure 20C). People were, however, biased to choice the cued option (Figure 20D). In the gambling frame, the bias parameter was significantly above and below 50% (when the cue was in the center) in the right and left cued condition respectively, and in the perceptual frame, the bias parameter was significantly above 50% in the left condition.

Overall, the parameter estimates from the classical drift diffusion model were unable to capture differences in gaze exposure on the baseline drift rate across tasks. From this set of results, we would erroneously conclude that the cue simply has a priming effect, but does not affect the rate of evidence accumulation. However, the attention drift diffusion model shows that not only does the exogenous cue prime participants to pick the cued option, the cue also leads to differences in gaze patterns, which then affects the rate of information accumulated from the two options.

APPENDIX D: Attention Drift Diffusion Model Parameter Estimates for Study 2

The interrogation version of the attention drift diffusion model was fit to study 2 and yielded the parameter estimates in Figure 20.

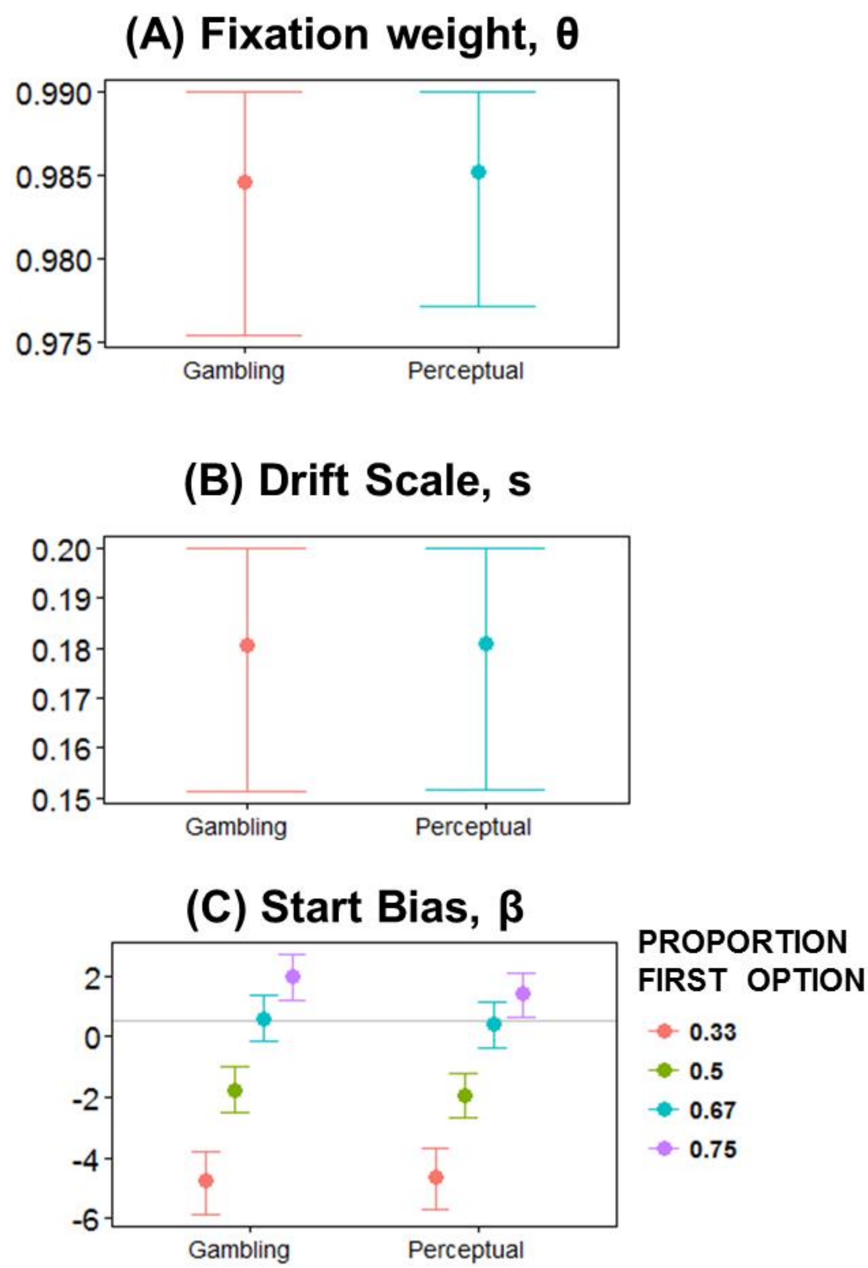

Figure 21. Parameter estimates of the attention drift diffusion model for Study 2.

Notably, the fixation weight is close to 1 across both tasks frames, indicating that the process approximates the classical drift diffusion model. This is unsurprising, as the fixation weight parameter is meant to index moment-to-moment relative divided attention, which occurs in Study 1 but not in Study 2. Instead, the relative gaze duration manipulation in Study 2 is at the aggregate level across the entire trial, and participants are able to devote their full attention to the single stimulus option appearing at each time point onscreen.

APPENDIX E: Study with Repeated Information

A total of 32 participants were run in the gambling condition in this study, over the 8 conditions outlined in Table 4. The procedure was similar to the second study. However, each item was presented only once, and in some of the conditions (16R), a series of 8 unique dot frames were repeated to generate a total of 16 frames. Participants were not told of this manipulation, and were simply asked to decide if they preferred the red or blue option.

Table 4. Stimulus duration levels in the follow-up third study.

The repeated frames are indicated by 16R, which mean that a series of 8 unique frames were repeated again. The rest of the frames were unique.

ID	**Number of switches**	**Number and type of frames**			**Duration of first option**
		Total	**Set 1**	**Set 2**	
1	1	16	8	8	50%
2	1	24	8	16	33%
3	1	24	8	16R	33%
4	1	24	16	8	67%
5	1	24	16R	8	67%
6	1	32	16	16	50%
7	1	32	16R	16	50%
8	1	32	16	16R	50%

Repeating the stimulus frames did not have an effect on choice. The results corroborate the second study, and show that participants were more likely to choose the option that was presented for a longer time (Figure 22).

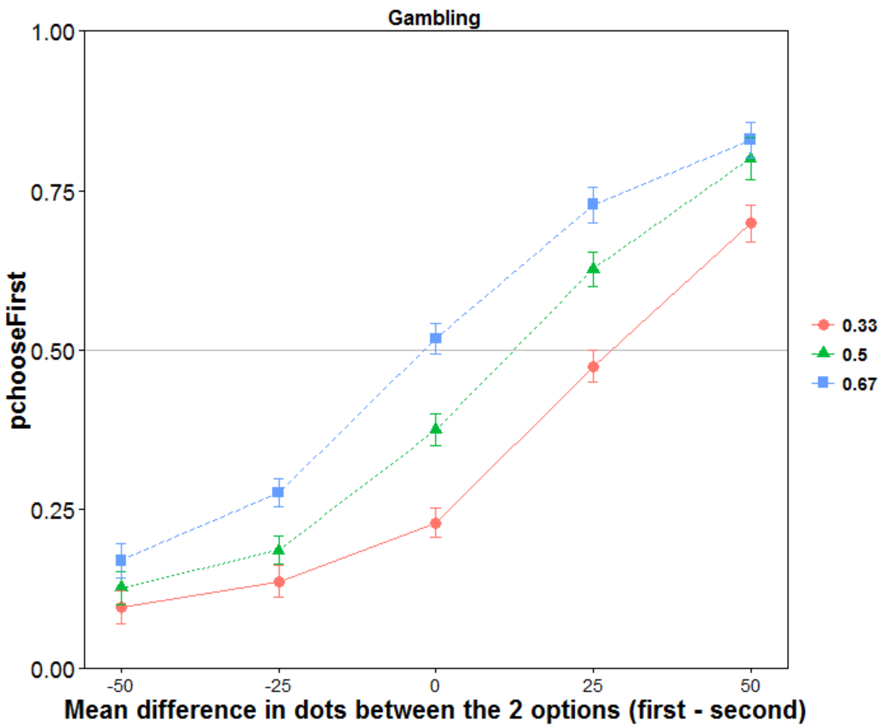

Figure 22. Probability of choosing the first option in Study 3.

Data and corresponding psychometric curve describing the probability of choosing the first option against the difference in option attractiveness in Study 3. The data was conditioned by the relative duration of the first option (line colors and shape).

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