THE SIGNAL FOR GOOD NEWS AND VALUE OF INFORMATION IN HUMAN CHOICE BEHAVIOR

by

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Abstract

Surprisingly, pigeons have been shown to sacrifice food rewards to get information about the upcoming outcome when making choices in a delay decision task. For instance, when choosing between an option which offers a reward 100% of the time after a delay (e.g. 10 s), versus an option that gives rewards only 50% of the time after the same delay but gives information about the reward (pecking it leads to a color that signals reward / no reward), pigeons sometimes prefer the 50% option. However, when the information is not immediate (e.g. it takes a few seconds after the peck for the color change to occur) pigeons almost exclusively choose the 100% option. Here, we tested if this same preference for immediate information would be evident in human choice behavior. In four experiments we adapted the pigeon task to a human reaching choice task to test two questions: 1) Do humans prefer information over no information, especially when it is received immediately? 2) Do humans show an asymmetry for information biased by valence, preferring good news and avoiding bad news?

In Experiments 1 (n = 30) and 2 (n = 30) participants reached to choose between shapes on a touchscreen that either revealed the outcome (turned green for good or red for bad) or not (stayed the same color) and did so either immediately or after a delay (2 s for E1, 4 s for E2). Unlike pigeons, the results show that humans do not prefer information (immediate or delayed), instead choosing almost exclusively based on the probability of payoff. In Experiments 3 (n = 20) and 4 (n = 25), participants again reached to choose between shapes, a “good news” shape that sometimes changed color when the outcome was good, a “bad news” shape that sometimes changed color when the outcome was bad, and a neutral shape which never changed color. Here we see a significant preference to choose “good news” shapes and avoid “bad news” shapes. These results support the Signal for Good News (SiGN) hypothesis which argues that receiving a signal of good news in a 50/50 gamble task is more rewarding because it causes a large positive reward prediction error. However, our results also show that, unlike pigeons, humans avoid bad news, suggesting loss aversion may spill into the information domain.

Preface

This thesis is an original work by Jeffrey Sawalha. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “ACE 1”, Pro00059044, 12/26/2017.

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1.0) Introduction

Imagine the agony of waiting to find out if you’ve received a scholarship award. The uncertainty of a future outcome can be a real dilemma. We may try and alleviate this cloud of uncertainty by checking our emails daily hoping for an update or asking fellow students if they have heard anything about their applications. In other words, we are driven to seek information about a future outcome to reduce uncertainty (Ligaya, Story, Kurt-Nelson, & Dolan, 2016). In the above example, finding out about your scholarship status can be defined as the “information”. Seeking this information can be intrinsically rewarding to people because it reduces uncertainty about an eventual outcome. This is based on the Uncertainty Reduction Theory (URT), which states that there is a positive relationship between certainty and information seeking (Kellerman & Reynolds, 1990) such that if someone is uncertain, they may engage in information seeking behaviors. The core principle is that humans do not like being uncertain about future outcomes.

Returning to the scholarship analogy, some people may seek information immediately about their outcome rather than to wait for days or months. This notion falls under the Temporal Discounting Theory (TDT), which states that receiving a reward now is more valuable than receiving that same reward later. That way, they are working to reduce their uncertain cognitive state faster instead of letting it fester. With the advance of communication and technology in today’s world, receiving information in a timely manner about future outcomes is becoming extremely valuable for humans (Kellerman, Reynolds, 1990). This is especially true when the information is instrumental of the outcome (Foley, Kelly, Mhatre, Lopes, & Gottlieb, 2017). Instrumental information is defined as information which can be acted upon towards a goal. However, there is growing evidence that humans assign significant value to non-instrumental information as well (Eliaz & Schotter, 2010). Non-instrumental information is defined as information which cannot be acted upon. Seeking information about your scholarship is non-instrumental in nature because you cannot act on the new information you've acquired. Finding out that your fellow graduate mate received their scholarship will not change your future outcome. Regardless of the type of information, seeking information immediately should be a main priority to reduce overall uncertainty about an outcome in humans. The URT and the TDT are two theories we will use to examine the value of information about rewards in humans, particularly in our first two experiments.

Another important aspect of the value of information is the type of information we're seeking. Is all information equally desirable to humans? Would you actively seek information about your scholarship if you knew your chances were slim to none? Is no information better than bad information? The valence of information may dramatically change the course of action someone is willing to take when seeking out a potential reward. Therefore, it is important to look at the impact of negative and positive information about future outcomes. We know that losses are handled differently than equal gains in humans, through a theory known as loss aversion (Sabrina, Fox, Trepel, & Poldrack, 2007; Tversky & Kahneman, 1992). If information is treated the same way as reward in humans, perhaps there may be the same aversion for bad information as there is for negative future outcomes. If we might predict loss aversion to govern our reaction to negative information, another theory known as the Signal for Good News (SiGN) might apply to positive information. The SiGN asserts that receiving a signal of good news in an unknown gamble may be more rewarding than receiving good news in a scenario where the reward is guaranteed (Mcdevitt, Dunn, Spetch, & Ludvig, 2016). This signal of good news acts as a conditioned reinforcement when you unexpectedly receive positive information about a reward as opposed to expecting it. That is, receiving good news about your scholarship when you had a low chance of winning might feel more satisfying because it was unexpected than if you had a high chance of winning. These two theories will also serve as reference for establishing the value of information in humans, particularly in our last two experiments.

This thesis aims to establish the intrinsic value of immediate information through motor decision making, particularly as it pertains to a reward outcome. How valuable is immediate information about future outcomes to humans? Does positive or negative information affect our behavior? How similar are our behaviors to that of other species? There are numerous animal studies that confront questions about the value of information, but few human studies are dedicated to this. I posit that immediate information, regardless of the valence, is more valuable to humans than delayed information when performing motor decision tasks. This includes receiving bad information over no information. In some cases, the information may be as valuable as the reward itself. The research presented here is grounded in behavioral decision making. However, there is a neurological basis for how information is processed in the brain relative to rewards. Therefore, to set the groundwork, the first part of this introduction examines the neurological underpinnings of how rewards are processed in the brain. The second part examines the theories on why information is considered valuable in animal literature. The third section looks at neurological and behavioral evidence from choice tasks on monkeys and pigeons. The final section transitions to behavioral preferences in humans for information.

1.1) Reward circuits in the brain

Since my research hypothesis claims that information can be as valuable as rewards, it is worth examining how rewards themselves are processed in the brain, specifically, the dopaminergic system. The mesolimbic dopamine pathway in the human brain is largely responsible for processing rewards, pleasure, and addictions (Oscar Arias-Carrión, 2010). This specific area has been examined in people with various types of addictions (drugs, food, sugar etc.) and mental disorders (major depressive disorder, schizophrenia) (Claudio A. Naranjo, 2001). More notably, it plays a role in mediating the value of rewards like food, sex, social reinforcers, and pleasure (Berridge & Robinson, 1998). The mesolimbic pathway consists of the pre-frontal cortex (PFC), the nucleus accumbens (NA), and the ventral tegmental area (VTA). The output of this system involves the release of dopamine from the VTA, a catecholamine derived neurotransmitter, back to areas like the NA and the PFC (Lampros Perogamvros, 2012). Figure 1.1 shows the dopaminergic pathway and all the areas dopamine reaches from the VTA.

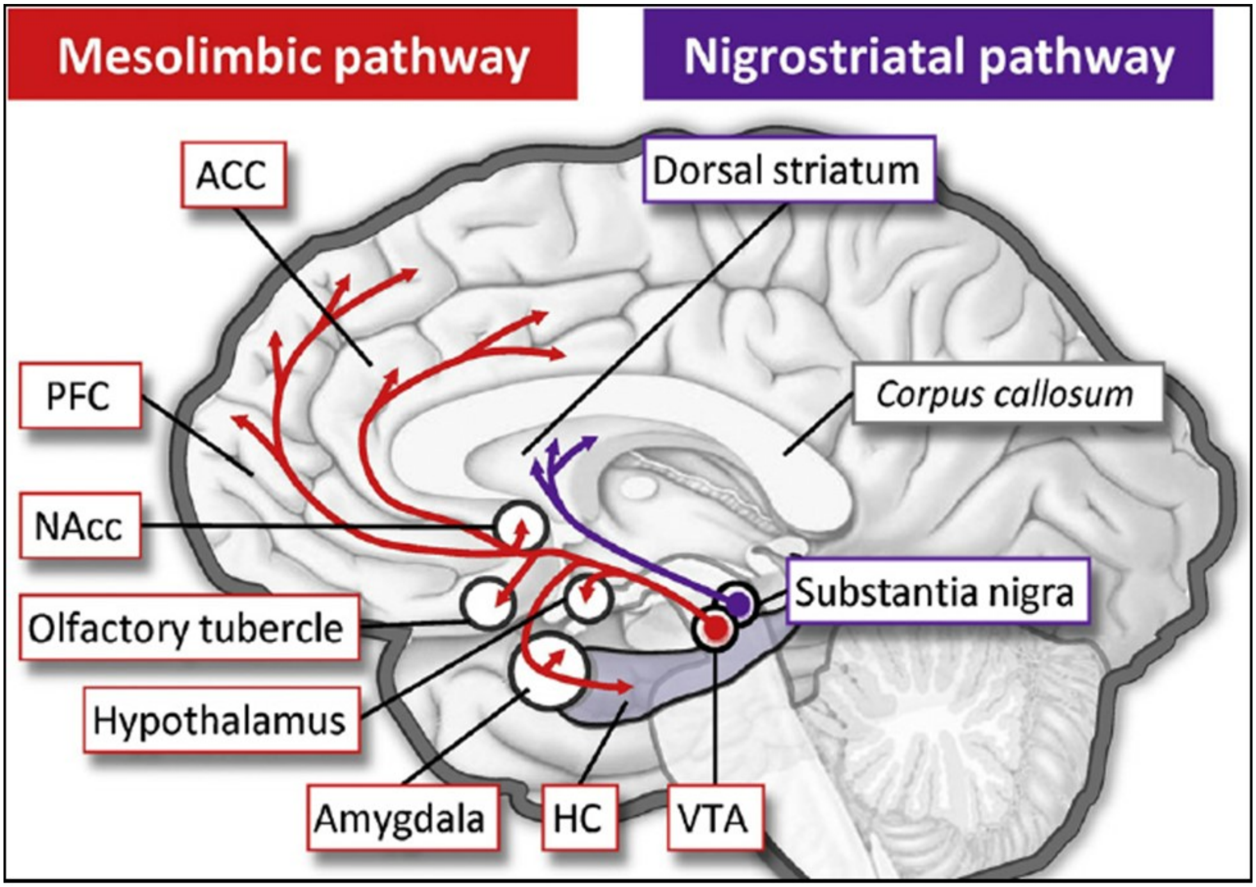

Figure 1.1) Overview of the Mesolimbic and Nigrostriatal pathway in the human brain. Dopamine has feedback loops for both the mesolimbic and nigrostriatal pathway.

Specifically, dopamine is released back to the PFC and this area specifically modulates reward, reward expectancy and prediction errors. (Lampros Perogamvros, 2012). Testing on the mesolimbic pathway in humans has its ethical restrictions, so animal models have been widely used to make advances in this area. Therefore, researchers have sought out species that contain similar mesolimbic structure to humans, namely, rats and monkeys (Ongur & Price, 2000).

1.2) Information as rewarding

Now that we have a cursory understanding of how reward is processed in the brain, it is important to make the case for why information may itself be rewarding. Across different species, information about future outcomes has been shown to be inherently valuable (Bromberg-Martin & Hikosaka, 2009). There is neurological and behavioral evidence suggesting that both non-instrumental and instrumental information is preferred over no information or even food rewards in pigeons and monkeys (Foley, Kelly, Mhatre, Lopes, & Gottlieb, 2017; Bromberg-Martin & Hikosaka, 2009; McDevitt, Spetch, & Dunn, 1997). From these findings, many principle theories stemmed out as to why information holds such value to animals. Among these theories, the Uncertainty Reduction Theory (URT) stands out as one of the prime predictors of information seeking behavior in animals and humans. For animals, the sheer vastness of environmental uncertainty shapes biological behaviors. Among these behaviors is the need to seek out information about uncertain biological scenarios, so the animal can reduce its level of anxiety (Inglis, 2000). Therefore, animals place a high priority on behaviors that reduce uncertainty, and attaining information is a primary reinforcer for this (Inglis, 2000). The ability to acquire food, escape predators, and find mating partners are just some of the outcomes that animals must strive towards in their everyday activities. Therefore, constant scanning for information about these outcomes become an instinctive part of behavior for them. Soon, these bits of information turn into conditioned reinforcers for positive outcomes, and can become a reward themselves (McDevitt, Spetch, & Dunn, 1997). Comparatively, the URT applies to humans who also behave in a certain manner to reduce uncertainty about their future outcomes. In addition to the scholarship example, there are a great deal of scenarios where humans seek out information about a future outcome to reduce their level of anxiety and uncertainty.

A second theory on the rewarding value of information involves time, either to enhance the reward of information to suppress it. Traditionally, it's been suggested that the value of a reward is temporally discounted the longer you wait to receive it. This is known as the Temporal Discounting Theory (TDT) (Green, Myerson, & McFadden, 1997). The idea is that the longer you must wait to receive a reward, the less subjective value it holds over time. For example, when given a choice between receiving $800 now, or $1000 in 6 months, most people prefer the first option, because time discounts the value of $1000 (Green, Myerson, & McFadden, 1997). If the value of information is held to the same standard as reward in the brain, then we should see similar temporal discounting trends.

As an interesting counter point to the TDT, other theories argue that some species "savour" a reward. Savouring refers to the correlation between longer temporal delays, and the increase in subjective value of a reward. The longer you must wait to receive a reward, the more rewarding it gets. It is analogous to waiting for a vacation you booked months prior. The anticipation of waiting for that trip is rewarding, and it is associated with positive utility. (Iigaya, Story, Kurth-Nelson, Doland, & Dayan, 2016). In this paper, Iigaya et al., (2016) put forth a reinforcement-learning model that predicted subjects prefer advance information of positive outcomes more when they had to wait longer for the rewards. In this case, opposite to temporal discounting, receiving delayed information may increase the intrinsic value of it for humans.

Thus, it is worthwhile examining the influence of delayed information as it pertains to information as a reward outcome.

As good information can be savoured in certain scenarios, anticipating bad information can be met with dread. Dread is defined as the anticipation of negative outcomes. Just as savouring good information increases the value of information or outcomes over time, dreading bad information can decrease the value of information or outcomes (Green, Myerson, & McFadden, 1997). Depending on the severity of potential bad information, humans may be averse to seeking information about their future outcome, thus decreasing the value of the information (Ganguly & Tasoff, 2016). In one experiment done by Ganguly & Tasoff (2016), humans were given the choice to reveal information about a future lottery by paying money. Even though this information was non-instrumental, subjects were more likely to pay for information about their lottery (Ganguly & Tasoff, 2016). In a second hypothetical experiment, subjects could pay to avoid being tested for herpes simplex virus type 1 (HSV-1) or the more severe type 2 (HSV-2). Subjects were three times more likely to avoid testing for HSV-2, suggesting that more aversive outcomes lead to more information avoidance (Ganguly & Tasoff, 2016). Here, it is evident that humans can behave differently when they are aware of what type of information they might be receiving. Therefore, it is worthwhile to test for possible asymmetries in how people treat good information and bad information. Humans may be enticed to seek out good information, especially when it is provided immediately, but also, they may actively avoid bad information.

1.2.1) Information seeking in pigeons

Already we have identified some pertinent questions with respect to whether information is intrinsically rewarding and if so, whether its reward operates in humans as it does in animals.

To further the comparative aspect, it is therefore useful to provide more detail about previous research into information seeking in other animals. Behavioral tasks for seeking information about future rewards has been examined in pigeons. Surprisingly, pigeons have been shown to sacrifice real food rewards to gather information about whether they are getting food (McDevitt, Spetch, & Dunn, 1997). In this experiment, pigeons made choices between a target that resulted in food 50% of the time after a delay (~30 seconds to receive food), but offered immediate information about the outcome (when pecked, target changed from red to white/yellow, "good news" color counterbalanced) when food would be dispensed or green ("bad news") when food would not be dispensed) versus a target that resulted in food 100%, but offered no additional information about the eventual outcome (when pecked, the target always gave "good news" and changed from red to white/yellow). In these circumstances, the pigeons preferred the 50% option (McDevitt, Spetch, & Dunn, 1997), even though it resulted in significantly less food. This condition was compared with a control condition where both targets offered no information, and here the pigeons exclusively chose the 100% target. Therefore, the authors conclude it is the introduction of information that causes the pigeons to deviate from the optimal preference of the 100% target toward the suboptimal 50% target (Mcdevitt, Dunn, Spetch, & Ludvig, 2016). Their behavior is suboptimal in the sense that they do not maximize their food rewards. Other studies have explored if this effect continues even if the probabilities of receiving food rewards is varied. An experiment conducted by Stagner & Zentall (2010) examined choice preference in pigeons with probabilities of 75% for uninformative targets, and 25% or 50% for informative targets. Pigeons continued to prefer the informative targets, and the difference between 25% and 50% was not significant. Furthermore, they performed another experiment with a 20% informative target versus a 50% uninformative target. Again, pigeons preferred the 20% target 87% of the time (Stagner & Zentall, 2010). It was only when the informative targets had a 5% chance or less, did the pigeons shift their preference to the uninformative targets. This study shows that pigeons are sensitive to probabilities, yet they are willing to sacrifice extreme discrepancies between food opportunities to receive information about the outcome.

Although pigeons may prefer informative targets over non-informative targets, they ultimately only prefer this information if it is received quickly (McDevitt, Spetch, & Dunn, 1997). In another experiment performed by McDevitt, Spetch, & Dunn (1997), pigeons again had to peck a screen that had two illuminated targets, one which resulted in food 50% of the time after a delay but immediately offered information, and the other which resulted in food 100% of the time after a delay but did not reveal any information. As discussed, pigeons preferred the 50% target over the 100% target. However, when a five second "gap" was inserted between the peck and the onset of the information for the 50% target, pigeons surprisingly shifted their preference to the 100% target. In fact, pigeons shifted their preferences any time the "good news" signal was delayed. That is, even though the reward outcome was identical, delaying the information was enough to shift preference away from informative targets. Figure 1.2 shows all the conditions that included a delay (McDevitt, Spetch, & Dunn, 1997). Thus, it therefore appears that rewards, and immediate positive information are both considered high priorities for pigeons.

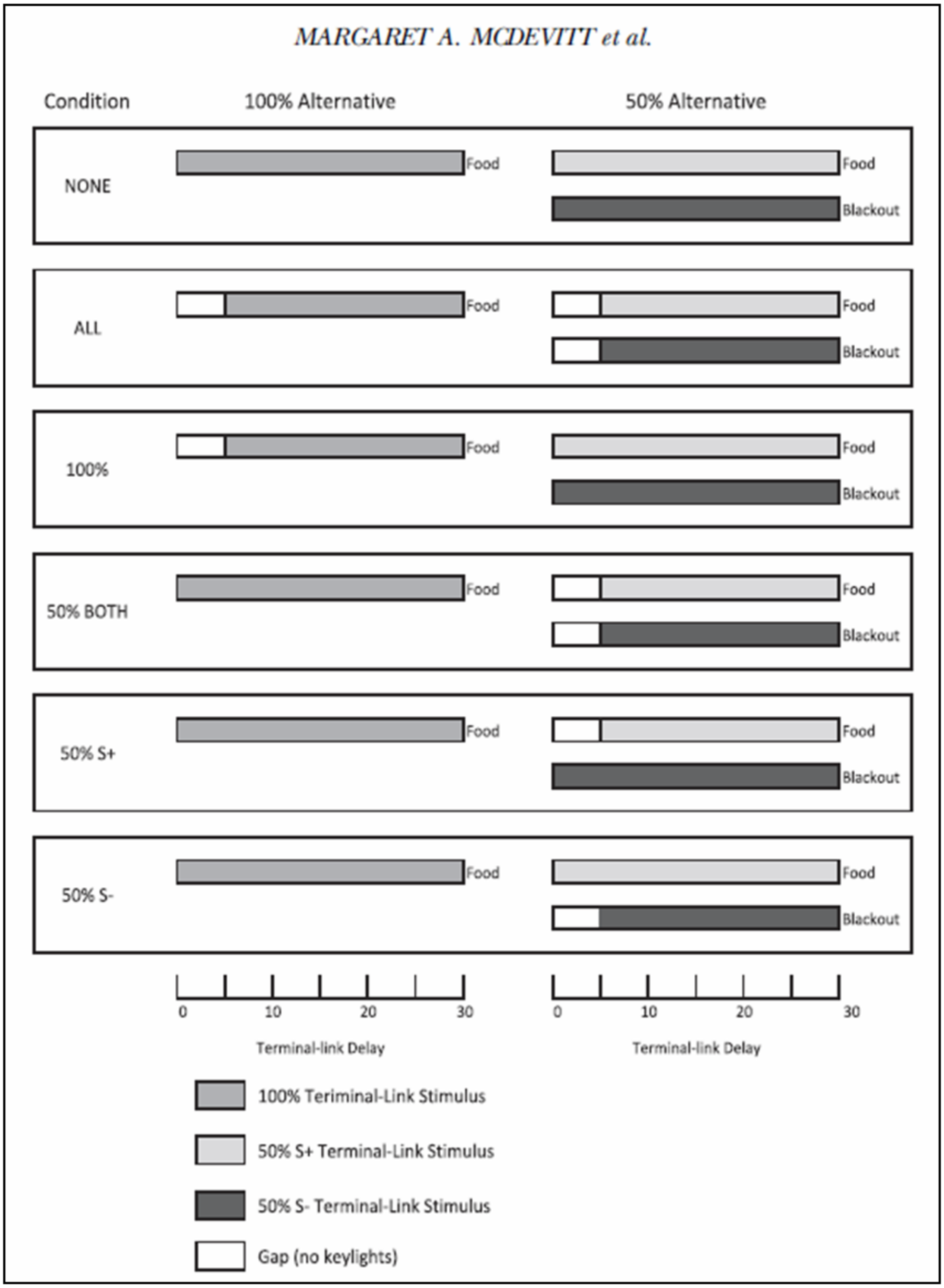

Figure 1.2) Delayed choice task conditions for McDevitt, Spetch, & Dunn, (1997). Pigeons chose between a 100% and a 50% alterative. The conditions with the white gap bars indicate a 5 second delay after the pigeon selected the initial-link stimulus. The duration of every trial lasted 30 seconds whereby pigeons would observe an informative signal, or a non-informative signal based on what target they selected.

1.2.2) Information seeking in the monkey brain

Pigeons appear to value immediate positive information so much so that they will forgo food reward. It is valuable, however, to see how information seeking appears in another animal species, namely monkeys, who share even more neural circuitry with humans. Of note, investigating information seeking in monkeys allow us to test whether the response to information gives rise to the same dopaminergic response we would expect to see for an actual reward. For example, in monkeys, phasic activation of dopamine neurons is seen when expecting a liquid reward (Fiorillo, Tobler, & Schultz, 2003). That is, when a monkey behaviorally prepares to receive a reward by licking its lips, and increasing saliva in the mouth, there is a burst in dopaminergic signaling seen in the mesolimbic pathway. Furthermore, the activation of dopamine neurons can account for the probability of receiving a reward (Fiorillo, Tobler, & Schultz, 2003). Dopamine neurons can monotonically encode the discrepancies between predicted rewards and actual rewards. By systematically varying the probabilities of receiving a reward, the authors noticed a trend in the phasic activation of dopamine neurons in the brain. Higher probability trials resulted in greater activation of dopamine neurons, whereas lower probability trials resulted in lower activation (Fiorillo, Tobler, & Schultz, 2003). This finding confirms that dopamine neurons are more excited when expecting a reward. It also confirms that dopamine neurons can monotonically encode the probability of receiving a reward. It is then worthwhile to ask the question: Can these dopaminergic neurons encode information about a reward?

Bromberg-Martin & Hikosaka shed light on how dopamine neurons respond to presence of rewards and information in the brain of macaque monkeys (Bromberg-Martin & Hikosaka, 2009). Two macaque monkeys were required to make eye movements towards 1 of 2 targets on a

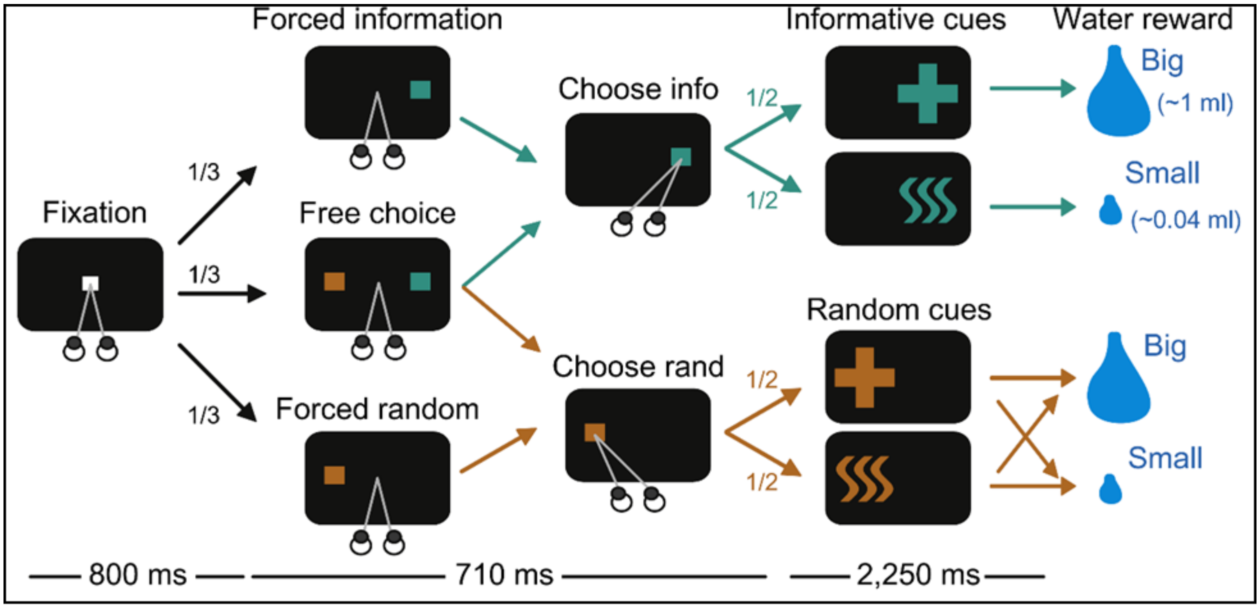

Figure 1.3) Frame-by-frame procedure of Bromberg-Martin & Hikosaka (2009) experiment # 1. Forced information, forced random, and free choice conditions were presented to two monkeys over ~150 trials each.

screen to receive a big water reward, or a small water reward. Looking at one target gave them accurate information (in the form of shapes) about the size of the water reward, and the other target gave them random non-information about the size of the reward. Figure 1.3 shows a frame by frame procedure of all conditions. There were forced target trials, where the monkeys were forced to see what each target revealed. Then, free choice trials were randomized among the forced trials, where the monkey could choose which target to look at. Single cell neural recordings were done simultaneously as the monkeys performed this task. Recordings were taken in the fronto-parietal cortex which involved areas like the VTA, NAc and the substantia nigra. Behaviorally, both monkeys almost exclusively preferred the informative targets over the non-informative targets in the free choice task trials (~100% for Monkey V, and ~80% for Monkey Z) (Bromberg-Martin & Hikosaka, 2009). This confirmed that these monkeys prefer to receive information about the size of a water reward over receiving no information at all. Neurologically, midbrain dopamine neurons signaled when expecting a large reward. These neurons also signaled when expecting information about a big water reward (Bromberg-Martin & Hikosaka, 2009). The authors provided evidence that behavioral preference is paralleled by neural preference for big water rewards and information about big water rewards. Thus, they showed that information about a reward is encoded in the same fashion as rewards themselves in mesolimbic pathway of monkeys. To summarize – both pigeons and monkeys show a preference for information and in monkeys, this is shown to correspond with a neural response like responses seen when the monkey receives an actual reward. However, several important questions need to be considered as we move into considering human information seeking.

1.3) Choice behavior in humans

Despite species differences, there are good reasons to believe that humans will show similar behavioral patterns consistent with valuing information. First, humans, like other species, are driven to reduce uncertainty about a future outcome (Kellermann & Reynolds, 1990). As mentioned earlier, the URT states that a lack of knowledge about something leads to information seeking behaviors. Consequently, having a surplus of information leads to abstaining, which often suppresses seeking behaviors. (Kellerman & Reynolds, 1990). Therefore, it is conceivable to think that humans will try to uncover more about an outcome quickly. Second, some theories would predict that, like pigeons, humans value the immediacy of a reward. Specifically, the TDT states that people will discount the value of a reward the longer they have to wait for it (Green, Myerson, & McFadden, 1997). Waiting to receive a reward can have less subjective value to a person than receiving the same reward right away. This has been studied extensively in addicts of nicotine, and alcohol. For example, Bickel, Odum, & Madden (1999) conducted a study on temporal discounting in addicted smokers. Neurologically, nicotine is a highly addictive drug because it bypasses the metabolism process (since it is inhaled, not digested), and can reach the brain within 10 seconds of inhalation (Bickel, Odum, & Madden, 1999). Therefore, the fact that people receive the “reward” of the nicotine so quickly is part of what makes it addictive. In a hyperbolic task (hypothetical money task), addicted smokers displayed more temporal discounting than ex-smokers or non-smokers. The authors concluded that the rapid effects of nicotine on the mesolimbic reward pathway can alter behavioral discounting of other rewards (Bickel, Odum, & Madden, 1999). If humans do find information intrinsically rewarding, perhaps it will also show discounting, being preferred only when it is available immediately.

Additionally, choice behavior in humans doesn’t always meet a rational, symmetrical explanation. One theory grounded in the asymmetrical nature of decision making is Prospect Theory (Tversky & Kahneman, 1992), one consequence of which is loss aversion. Loss aversion states that people exhibit a greater sensitivity to losses than equivalent gains when making decisions (Sabrina, Fox, Trepel, & Poldrack, 2007). For example, people will often reject gambles that offers a 50/50 chance at gaining or losing the same amount of money. It is only when presented with options where the gains are twice as large as the losses that most people will commit to the gamble. (Tversky & Kahneman, 1992). Loss aversion is a pattern of behavior that is seen from capuchin monkeys to adolescent children to adults (Sabrina, Fox, Trepel, & Poldrack, 2007). The idea that losses hurt more than gains may stem from neurological origins. Neural responses in the mid brain dopaminergic system show increased activity as potential gains increased. Likewise, potential losses are represented by decreasing activity in these same gain-sensitive areas. However, potential losses may permeate to distinct emotional regions in the brain such as the amygdala or anterior insula (Sabrina, Fox, Trepel, & Poldrack, 2007). It is suggested that potential losses can drive negative emotions, which can lead to fear or anxiety (Sabrina, Fox, Trepel, & Poldrack, 2007). If the reward derived from receiving information is encoded in the same dopaminergic system as gains/losses, perhaps loss aversion will apply to informative signals as well. As a potential primary reinforcer, receiving equally bad information about future outcomes may be met with aversive behavior in humans. If true, we can expect an asymmetrical distribution, where people may prefer to seek good information, but will show a greater preference for avoiding bad information, since it can additionally induce fear/anxiety. This would stand in contrast to URT, where any information is good in the sense that uncertainty is reduced.

Another theory that runs perpendicular to loss aversion is the Signal for Good News Hypothesis (SiGN) (Mcdevitt, Dunn, Spetch, & Ludvig, 2016). The SiGN stems from some of the pigeon literature described above and suggests that receiving a signal of good news in a 50/50 gamble task is more rewarding than receiving a signal of good news in a task where pigeons are guaranteed food. That is, SiGN contends that in a task where food is guaranteed upon pecking a target, pigeons will establish a reference point (they expect to receive food upon pecking this target). From there, pecking that target again will not cause a shift in their reference point because the food is expected every time. Compare that to a target that offers a 50/50 chance of food and provides information about the outcome. Pigeons will learn that a reference point falls within getting a reward and not getting a reward. Thus, when receiving good news in a signalled target, pigeons shift their reference point in relation to the local context. This shift causes the signalled target that reveals good news to act as a conditioned reinforcer, making it more desirable than the guaranteed food target. This is what drives the seeking of immediate positive information in pigeons. They find more intrinsic reward in getting a good news signal on a 50/50 target because it shifts their local reference point, rendering the signal a conditioned reinforcer. By comparison to good news, SiGN suggests that bad news offers no role other than to create uncertainty (Mcdevitt, Dunn, Spetch, & Ludvig, 2016).

This hypothesis can be translated toward human behavior. For example, imagine expecting and knowing exactly what you're receiving for a birthday gift from a loved one. You will enjoy receiving the gift but will have created a reference point for what you're getting. Now, imagine that you unexpectedly receive a gift that you like from someone else, and you do not know what the gift is. Receiving an unknown gift by surprise is more intrinsically rewarding than expecting a gift you already know about. This may be due to a shift in reference points. By suddenly receiving a surprise, your reference is elevated to a new state, making the gift more subjectively rewarding. In this sense, receiving a good news signal is reframing the reference point in a gambling task, because the previous local point may be the neutral signal. We intend on testing each of these behavioral theories in humans to see first, if humans value information and, if so, is there an asymmetrical bias towards preferring good information or avoiding bad information.

1.4) Motivation, Hypotheses and Predictions

The overall goal of this project is to explore information seeking behavior in humans and relate the findings to previous animal literature. First, we want to examine whether human subjects will exhibit the same behavior as pigeons (McDevitt, Spetch, & Dunn, 1997) and sacrifice reward for information (Experiment 1). However, given that humans are likely more sensitive than pigeons in tracking total reward, and that information seeking was observed in monkeys when the reward outcome was equivalent (e.g. 50/50) across information and no-information choices (Bromberg-Martin & Hikosaka, 2009), we will run a second experiment where we look for information seeking in the absence of a reward asymmetry (Experiment 2). These two experiments test the theory of URT while also testing for the effects of delay in a motor decision making task. According to the URT, humans should value any information, good or bad, over no information and this preference may be strong enough to result in them not maximizing expected gains. With respect to delay, these experiments may provide partial evidence for either the TDT or the savoring / dread hypotheses. That is, the URT combined with the TDT predicts that humans will prefer any immediate information over waiting (e.g. like pigeons).

However, as described above, perhaps humans only value information when it is providing good news (informs of a positive outcome) rather than bad news (informs of a negative outcome). This relates to both the SiGN theory as well as loss aversion. That is, perhaps good news is all that is important (e.g. SiGN) or maybe, bad news is more aversive (e.g. loss aversion in the information domain). Experiments 3 and 4 will therefore assess the validity and degree to which loss aversion or the SiGN theory can explain human choice behavior in our simple motor decision making task. In our third experiment, we will specifically test whether a preference for information is seen exclusively for "good-news" targets. Likewise, we will examine if humans actively avoid bad news, to the extent that they'd prefer no information over bad information. If true, perhaps an asymmetry of preferences develops, where subjects may prefer good news more than they avoid bad news (the SiGN prediction) of vice versa (the loss aversion prediction). Finally, in our fourth experiment we intend to push this test of valanced information even further to see if good-news-seeking exists even when the value of the good information is reduced by giving reward feedback every trial.

In each of the four experiments, human subjects will perform a decision-making task by reaching out and touching shapes on a screen for points. The goal of is to collect as many points as possible, so that at the end of the experiment, subjects can trade in their points for snack rewards. Experiment 1, which is used as a template for the other experiments, is a 2 x 2 factorial

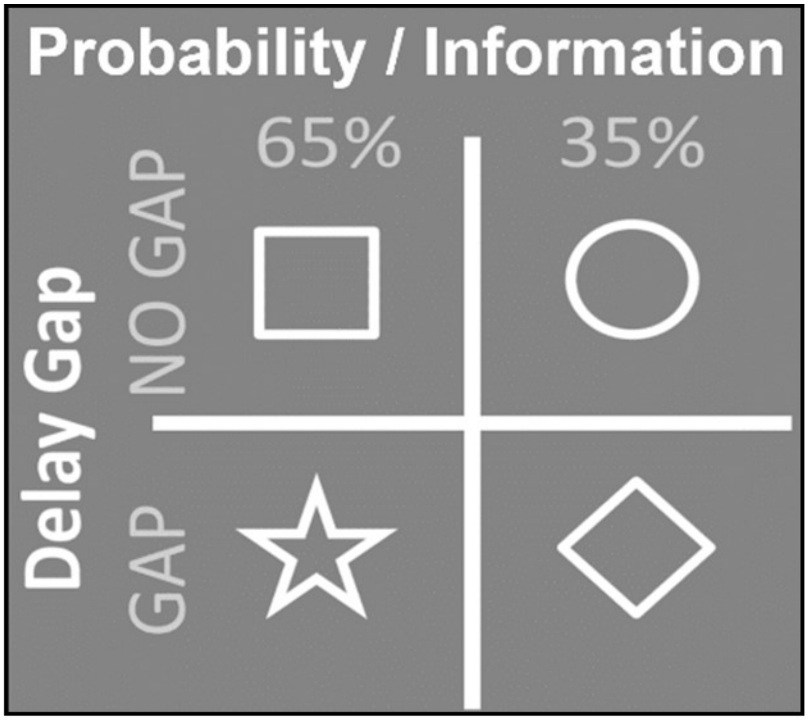

Figure 1.4) 2 x 2 factorial design for Experiment 1 and 2. Probability contingencies serve as one factor, and the presence of a delay serves as the other factor. In Experiment 2, the contingencies changed to 50/50%.

design (see figure 1.4), where one factor is information / reward (65% reward, non-informative vs 35% reward, informative) and the other factor is delay/gap (change color immediately vs change color after 2 s). Each of the 4 cells in the 2 x 2 design is represented by a choice target (shape) and all possible non-duplicate pairs (6 total) will be presented, as well as some single shape trials to make sure participants choose all the shapes some of the time. Our primary measure will be choice percentages to each shape in each pair to see if there is a preference for the informative shapes and whether this preference is abolished with delay. If humans are like pigeons, then we would expect them to select the informative, low-probability shape, but only when it revealed information immediately. However, we predict that humans will show a greater sensitivity to reward outcomes and will not sacrifice points for information. With respect to delay, we anticipate that our participants will prefer to receive feedback immediately versus after a delay, but do not predict an interaction with information, since we believe information will not drive behavior in this experiment.

Given our belief that humans will be sensitive to reward outcome differences, and this will override any preference for information in Experiment 1, Experiment 2 will replicate Experiment 1, but will have an identical reward probability of 50% for each of the 4 shapes. Thus, it is still a 2x2 design, but now the factor of information is not conflated with reward probability. Given this shift, we now predict humans will show a preference for the informative shapes and predict that this will interact with delay such that shapes giving immediate feedback, and especially immediate information will be selected more often than shapes giving delayed feedback.

As described above, Experiments 3 and 4 will test if the valence of information shifts preferences. Thus, in these experiments we plan to remove delay and only present three shapes: a shape that, when touched, immediately turns a neutral color (baseline, non-informative shape); a shape that, when touched, sometimes reveals if a positive outcome will occur (good-news shape); and a shape that, when touched, sometimes reveals if a negative outcome will occur (bad-news shape). We will then present all non-duplicate pairs (3 total) and some single shape trials. Experiment 3 will withhold the presentation of the point reward on every trial, and only give feedback after each block of trials, while Experiment 4 will give the point reward on every trial, making the information less valuable. Since we are predicting that our participants will show a preference for information, we believe this will be even stronger when that information is exclusively good. Depending on which theoretical framework is most accurate, we might predict 3 different patterns of choice behavior in these experiments: If loss aversion extends to human's preference in the information domain and is the dominant factor affecting decisions, then avoiding bad news will take precedence and drive behavior most strongly. If the SiGN hypothesis is more dominant, then behavior should be most driven by seeking positive information, with little to no avoidance of the effect of bad news. Finally, if both the SiGN hypothesis and loss aversion are at play then there should be no strong preference for either valanced choice.

2.0) Methods and proposed experiments

2.1) Methods common to all four experiments

2.1.1) Apparatus

A participant was seated in front of a 42-in. screen (1024 × 768-pixel resolution, 60-Hz refresh rate). Prior to the training trials, an adhesive reflective marker was placed on the nail surface of the right index finger for each participant, this marker was monitored by 6 OPTITRAK cameras above the task area. A "start" position marker was placed 10 cm from the front edge of a table, and laterally centered in the middle of the table they were seated at. Subjects touched the TV screen that was 40 cm away from the start position. The program ran on a 2016 version of MATLAB (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007; Chapman, Gallivan, Wong, Wispinski, & Enns, 2015) while the motion tracking information was relayed to MOTIVE (Natural Point; Corvallis, Oregon, USA). Subjects were asked to take off all reflective jewelry to ensure reflective surfaces did not interfere with OPTITRAK equipment. The OPTITRAK equipment was re-calibrated at the start of every testing day to ensure proper reliability of the motion capture data.

2.1.2) Subjects

Subjects were recruited from the University of Alberta research Psychology participation pool. These students are usually within the first 3 years of their undergraduate degree and are required to participate in ten hours of experiments around the university campus. All subjects recruited for each experiment were right handed, had English as their first language, and had proper or near corrected vision. All subjects signed the informed consent sheet. Those who objected to performing the experiment conducted an alternative assignment for research credit. Subjects were told they were going to reach out and select between shapes that appear on the screen. They were told the goal of the experiment was to collect as many points as possible, and at the end of the experiment, all points would be traded in for snack rewards at the end of the experiment. Each subject has a script read to them that will explain the nature of the task. This ensured that subjects were consistently being told the proper instructions to improve the validity and reliability of this experiment.

2.1.3) Procedure

Initially, the touch screen displayed a blank white canvas. A trial began when the participant placed their right index finger on the start position, at which time, a small fixation circle was displayed in the middle of the touch screen. The fixation was jittered to randomly appear somewhere between 500-1500 milliseconds (ms). This fixation was standard for all trials in this experiment. After fixation, participants heard a beep and one or two shapes appeared 9 cm away from the left and/or right of the fixation circle. The size of the four shapes (square, star, circle and cross – note only square, star and circle used in Experiments 3 and 4) were determined such that their interior area matches the area of circular target 2-cm in diameter and all shapes started filled in white with a black outline (Chapman et al., 2015). The subject had 100-3000 ms to touch one of the shapes. If the subject did not reach within the 3000 ms time limit, the screen displayed “Time Out” in red font, and the next trial began. If the subject reached before or within 100 ms of the beep, the screen displayed "Too Early" and the next trial began. If the subject egregiously misses either shape, the screen displayed "Miss", and the next trial began.

In each experiment, there was a set of training trials where subjects reached and touched single shapes on the screen. This ensured they learn how to perform the movement, as well as examining which shapes give rewards and information. At the end of the training block in some experiments, subjects were asked to subjectively report how often (in %) each shape rewarded them with points. In experiments 1 and 2, subjects were given this subjective report only at the end of the experiment. In experiments 3 and 4, they filled out the subjective report questionnaire twice. Once, right after the training trials and once after the experiment.

2.2) Experiment 1

Experiment 1 was a human adaptation of the McDevitt et al., (1997) pigeon experiment. Two of the four shapes were randomly assigned to be high probability shapes that offered a 65% chance of attaining points but revealed no information about the outcome (turn blue, which is a non-informative color). Likewise, two shapes were randomly assigned to be low probability shapes that offered a 35% chance at attaining points but revealed information about the outcome (turn green = +10 points, turn red = 0 points, see figures 1.4 and 2.1). For both the high and low probability shapes, one was randomly assigned to change color immediately, and one was randomly assigned to change color after a delay. All possible non-duplicate pairs (6 total) were shown to participants in both possible configurations (e.g. which target is left and right per pair) for a total of 12 unique pair presentations, each of which were presented 25 times across the entire experiment. In addition, each individual shape was presented by itself, in each location (8 total unique single target presentations) 10 times across the entire experiment. Combined, this gives 380 experimental trials that were presented in a random order across 10 blocks of 38 trials. Prior to these experimental trials, 24 training trials (each single shape presented in each location 3 times) were conducted but not analyzed.

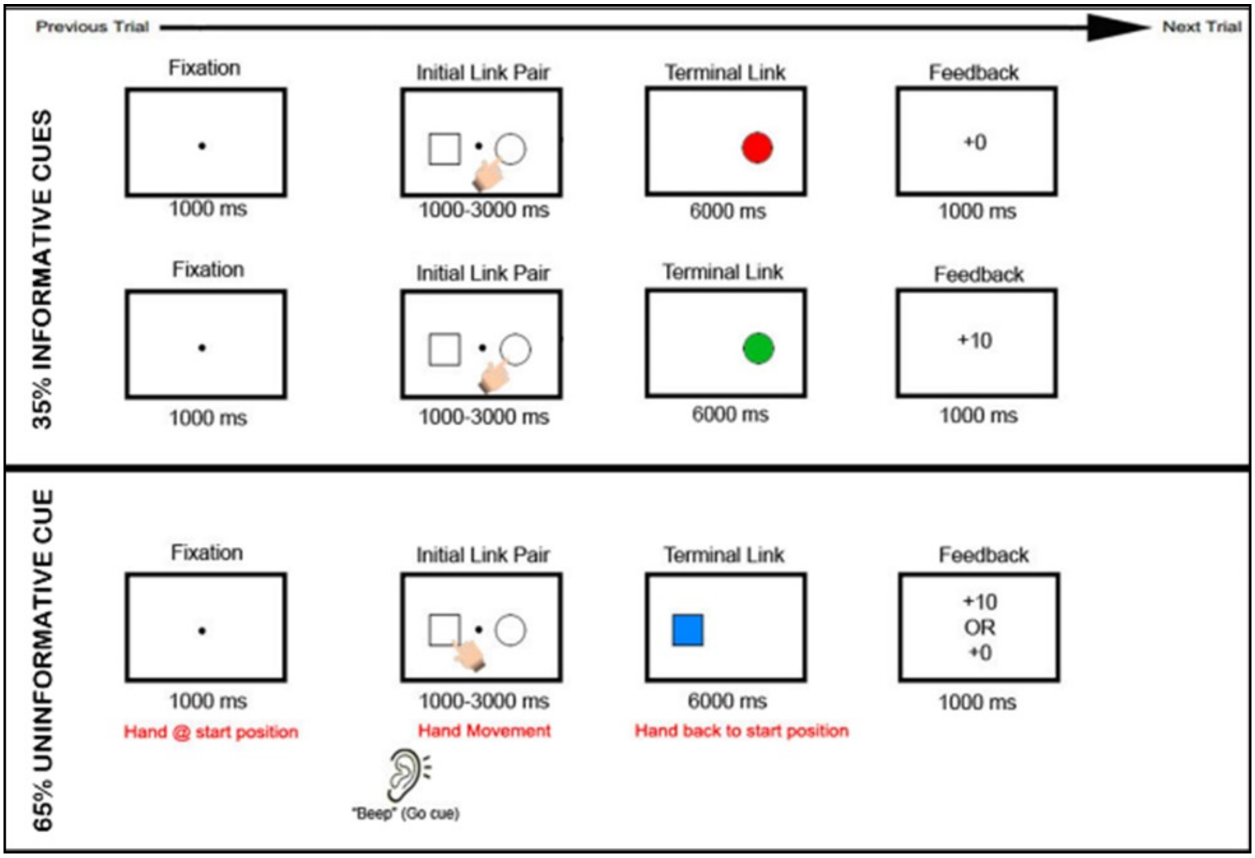

Figure 2.1) Non-delay condition procedure Experiment 1. The top bar displays the informative no delay frame-by-frame procedure. An informative shape selected between 1000-3000 ms will change to a red or green color, which indicates whether the subject will receive +10 points for that trial or not. The bottom bar represents the no-delay, non-informative condition. A non-informative shape will turn blue, which does not indicate whether points will be awarded or not.

When selected, high probability (65%) shapes turned blue, which revealed no information about future point rewards. Low probability shapes turned either red or green, indicating the success or failure of getting future point rewards. Refer to figure 2.1 for a frame-by-frame procedure of the no gap condition. If the subject reached towards one of the delay shapes, once selected, there was a 2000 ms delay of color presentation. The onscreen stimuli remained for 2000 ms before the delay shape filled in with a color. That is, no visual feedback was offered to suggest that the subject selected a shape for 2000 ms. 6000 ms after target selection (so, 4000 ms after color change for a delay shape) numerical feedback (e.g. +10 or +0) was be revealed for 1000 ms before the next trial begins. Feedback was always displayed in black font, at the center of the screen to control for potential color confounds with the information colors.

2.3) Experiment 2

Experiment 2 maintained the same experimental design as Experiment 1 but with a few major changes. First, the probability contingencies went from 65 / 35% to 50 / 50 %. We removed this potential confounding effect because humans may be more sensitive to probabilities than pigeons. Second, for the delayed shapes, we increased the onset of color presentation from 2000 ms to 4000 ms. A subject who selected a delayed shape waited 4000 ms before seeing the shape filled in a certain color, then 4000 ms until they received numerical feedback on whether they attained points for that trial. This increased the selection to feedback time to 8000 ms for all shapes (including immediate shapes). To account for the added time while keeping the experiment within an hour, we reduced the number of paired trials to 20 per configuration (240 total), the number of single trials to 5 per configuration (40 total) and the number of practice trials to 2 per target per side. This led to a 16-trial training block (not analyzed) followed by 10 blocks of 28 trials, randomly ordered.

2.4) Experiment 3 and Experiment 4

As explained, Experiments 3 and 4 were designed to test for asymmetries between the treatment of good and bad news. Therefore, we reduced the number of shapes to 3 and randomly assigned them to one of the following behaviors: a non-informative shape, that rewarded points 50% of the time, but always turns blue when touched; a “good” news shape, that rewarded points 50% of the time, but of that 50%, 25% of the time it turned green and 25% it turned blue; and a “bad” news shape, that rewarded points 50% of the time, but of the 50% of the time where not points were received, 25% of the time it turned red and 25% it turned blue. Since delay was no longer a factor in this experiment, all shapes changed color immediately, and stayed on the screen for only 1000 ms before moving to the next trial. This shortening allowed us to collect almost twice as many trials. All possible non-duplicate pairs (3 total) were presented in both Left/Right configurations (6 total) and repeated 40 times across the experiment (240 total). In addition, each shape was presented by itself in each left and right location (6 total) 40 times (240 total), for a total of 480 experimental trials, presented randomly across 10 blocks of 48 trials. A practice block with each shape appearing by itself in each location 8 times (48 total) preceded the experiment.

The only difference between Experiment 3 and Experiment 4 was whether we showed reward feedback on every trial. In Experiment 3, we enhanced the value of information and removed numerical feedback (during experimental trials) about point reward on each trial, instead of giving that feedback (running total score) only at the end of each block. Numerical feedback was presented during practice trials. In Experiment 4, coincident with the object being touched and changing color, numerical feedback was re-introduced (for both experimental and practice trials). Note, this rendered the color change completely irrelevant, but we wondered whether it may still drive behavior.

2.5) Dependent measures

We collected and analyzed the following dependent measures:

Choice Percentage: For each choice pair (initially, in each left/right configuration) we calculated the percentage of the time participants chose each shape in the pair, across all pair presentations.

Reaction Time: Defined as the time elapsed between the signal to move (auditory go-cue sound) and the first frame of detected motion (Gallivan & Chapman, 2014).

Movement Time: Defined as the time elapsed between the first frame of detected motion and when the subject touches the screen (Gallivan & Chapman, 2014).

Reach Area: For each pair (or single target), an average reach trajectory toward the preferred shape (e.g. the one selected most often in that pair, or, just the single target) was be generated when that shape is on the left and when it is on the right. Then, the area between these two curves for each pair was calculated (Gallivan & Chapman, 2014).

Subjective preference: For each shape, the difference between the subject's report of % payoff and the actual % payoff. For example, if a subject reported a 75% chance of attaining points for a shape that offered rewards 65% of the time, they're subjective preference would be +10%. In Experiments 3 and 4, subjects reported preferences twice — once after the training block, and once at the end of the experiment.

2.6) Data analysis plan

2.6.1) Choice Percentage

Experiments 1 and 2

Experiments 1 and 2 contain 4 shapes, and 12 pairs that were compared against each other. For choice percentage, we collapsed the mirror pair trials together, giving us 6 paired conditions instead of the original 12. First, we ran 6 one sample T-tests for each paired condition to detect if subjects showed any preference (e.g. statistically different than 50%). We used a Bonferroni correction to account for the error rate per comparison, which was a p-value of 0.05 divided by the number tests we ran (6). To test for broad differences across pairs, we conducted a repeated measure, one-way ANOVA (RM-ANOVA) with 6 levels represented by the paired conditions. Where the RM-ANOVA was significant, we ran all pairwise comparisons, corrected using Bonferroni's method.

Experiments 3 and 4

Experiments 3 and 4 contain 3 shapes, and 6 pairs that were compared against each other. For choice percentage, we collapsed the mirror pair trials together, giving us 3 paired conditions instead of the original 6. As we did for Experiments 1 and 2, we conducted 3 one sample T-tests against 50% for each paired condition to detect if subjects were choosing randomly, while using a Bonferroni correction. This was followed up by a RM-ANOVA with 1 level, represented by the 3 paired conditions where, if significant, corrected multiple comparisons were performed.

2.6.2) Reaction Time and Movement Time

For all experiments, the same statistical tests were conducted, the only difference being the number of levels being compared. For analyzing RT and MT, we ran three separate RM-ANOVAS. The first RM-ANOVA involved only single target trials, where we compared RT with the types of shapes and side of space. Therefore, this RM-ANOVA was a 2 x 4 design (for Experiments 1 and 2) or 2 x 3 design (for Experiments 3 and 4), with 1 factor being side of space, and the other factor being the type of shape (4 or 3 levels). The second RM-ANOVA analyzed paired trials where we sought to know if people react or moved faster to a specific shape in a paired condition, accounting for side of space, as well as their preference towards a given shape. For this, we had a three factor RM-ANOVA (6 x 2 x 2 for Experiments 1 and 2 or 3 x 2 x 2 for Experiments 3 and 4), where one factor represented the paired shapes (6 or 3 – each pair and its mirror is considered) the second factor was the side of space reached toward (2 – left or right), and the third factor was whether the subject was selecting a shape they preferred or not (this is based on their choice percentages). Significant main effects were followed up by examining all pairwise comparisons, using a Bonferroni correction. In the event of a 3-way interaction effect, we ran two, 2-way RM-ANOVAs, holding the preferred factor constant. One RM-ANOVA was a 6 x 2 or 3 x 2 design (shape pairs x side of space) containing only preferred shapes. The other RM-ANOVA was identical but contained only non-preferred shapes. If there was an interaction effect in either of those ANOVAs, we conducted two, one-way ANOVAS, holding the side of space constant. Again, one ANOVA was a 1 x 6 or 1 x 3 (shape pairs) for only left side shapes, and the other was for right side shapes. Our rationalization for hierarchical format was to titrate preferred from non-preferred shapes. We were more interested in examining if humans prefer reacting/moving faster to shapes that contained information. Lastly, we ran a third RM-ANOVA examining whether subjects reacted faster to single target trials or paired trials, accounting for side of space. This RM-ANOVA was a 2 x 2 design, where one factor represented the number of targets in a trial (single target vs. paired target), while the other factor was side of space. Again, if a significant p-value was found, we ran all pairwise comparisons post-hoc, and used the Bonferroni correction.

2.6.3) Reach Area

For all experiments, the same statistical tests were conducted, the only difference being the number of levels being used. The first test was a RM-ANOVA for single target trials with only one factor (target) with 4 (Experiments 1 and 2) or 3 (Experiments 3 and 4) levels. If a significant p-value was returned, we ran all pairwise comparisons and used the Bonferroni correction for all post-hoc tests. The second test for reach area examined paired target trials. A RM-ANOVA was used to examine area differences between all pairs (6 levels for Experiments 1 and 2, 3 for Experiments 3 and 4). If a significant p-value was returned, we ran all pairwise comparisons using Bonferroni's to correct for all experiments. Lastly, we ran a one-way RM-ANOVA, comparing the reach areas for all single target trials vs. paired target trials.

2.6.4) Subjective Preference

Experiments 1 and 2

We ran 4 one sample t-tests of the subjective values for each shape against 0%, since we calculated differences from reported frequencies to actual frequencies. The p-value for these 4 tests were corrected for using the Bonferroni correction. We conducted a one-way RM-ANOVA (1 x 4), comparing all four shapes to each other to examine differences among them. Main effects were followed up with corrected pairwise comparisons.

Experiments 3 and 4

With these two measures (reports pre-experiment and reports post-experiment), we conducted 6, one sample T-tests, comparing pre and post-experiment subjective preferences against 0 (per shape) and corrected for p-value. In addition, we ran a 3 x 2 RM-ANOVA, where one factor was the type of shape (3), and the other was the subjective preferences for pre- or post-experiment (2). Main effects were followed up with corrected pairwise comparisons and an interaction looked for changes across pair in both pre and post preference scores.

3.0) Results

3.1) Experiment 1 and Experiment 2

3.1.1) Choice Preference

For Experiments 1 and 2, one sample t-tests were conducted for all 6 paired shapes to examine if choice preferences were significantly different from chance (50%, significant at $p<0.05/6$). In Experiment 1, 4 of the 6 t-tests came back significant as seen in figure 3.1. Subjects preferred the non-informative (high probability), no gap shape 71% of the time when it was presented with the informative (low probability), no gap shape [$t(29) = 6.58$, $p < 0.0001$]. There was also a preference for the non-informative (high probability), no gap shape vs. informative, gap shape, which was selected 75% of the time [$t(29) = 7.31$, $p < 0.0001$]. In the no information, gap vs. information, no gap shape pair, subjects preferred the non-informative, gap shape 71% of the time [$t(29) = 6.02$, $p < 0.0001$]. Finally, in the no information, gap vs. information, gap shape pair, subjects also preferred choosing the non-informative, gap shape 77% of the time [$t(29) = 9.57$, $p < 0.0001$]. For Experiment 2, where probability was identical across shapes, none of the 6 one-sample t-tests came back significant, suggesting subjects were selecting at chance for each shape pair taken together. This pattern of results from Experiments 1 and 2 suggests individuals are most sensitive to probability contingencies over the value of information, or a delay.

In addition to the t-tests against 50%, a one-way RM-ANOVA was conducted on choice preference for each shape pair to examine if the magnitude of choice preference differed across shape pairs. In Experiment 1, the one-way RM-ANOVA was significant [$F(5,145) = 15.73$, $p < 0.0001$]. Post-hoc pairwise comparisons showed that the shape pairs with both non-informative shapes were different than all other combinations except for the shape pairs with both informative shapes. Consequently, the shape pairs with both informative shapes were different from the no information/gap vs. information/gap shape pair, the no information/ no gap vs. information/ gap shape pair, and the no information/no gap vs. information/no gap shape pair. Full details about the statistical results of these comparisons is visualized in figure 3.1 and available in Table 1.0. For Experiment 2, the one-way RM-ANOVA returned a non-significant F statistic [$F(5,145) = 1.22$, $p > 0.05$].

This finding supports the conclusion from the t-tests against 50% that in Experiments 1 and 2, subjects are sensitive to probability contingencies, since they preferred shapes in Experiment 1 that offered a higher probability of reward. This effect was absent in Experiment 2 because all shapes were given an equal probability of rewarding points. Counter to our prediction, the presence of a delay did not affect choice preferences across Experiments 1 and 2.

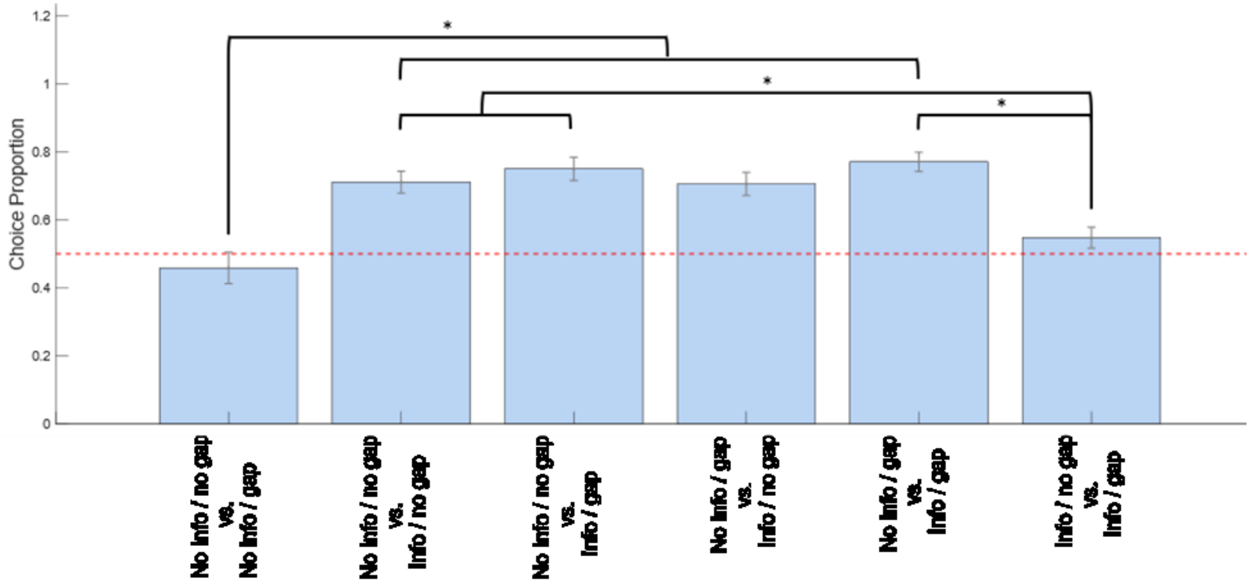

Figure 3.1) Choice preferences for Experiment 1. All conditions except No Info vs No Info and Info vs Info are significantly different from chance (t-tests against 50%). Loftus and Masson (1994) within-subject error bars are shown and represent 95% confidence intervals (CIs). Asterisks indicates significance of pairwise comparisons. Refer to Table 1.0 for p-values.

Table 1) Experiment 1 means and statistical tests

<table>
<tr><th>Measure</th><th>Test</th><th colspan="24">Condition</th><th>F</th><th>Pairwise</th></tr>
<tr><td rowspan="2">**Choice Preference**</td><td>*RM (1 x 6)*</td><td colspan="4">*No info/no gap* vs. No info/gap
M = 45.85%</td><td colspan="4">*No info/no gap* vs. Info/ No gap
M= 71.04%</td><td colspan="4">*No info/no gap* vs. Info/ gap
M= 74.95%</td><td colspan="4">*No Info/gap* vs. Info/ No gap
M= 70.54%</td><td colspan="4">*No Info/gap* vs. Info/No gap
M= 76.98%</td><td colspan="4">*No info/no gap* vs. Info/No gap
M= 54.71%</td><td>***</td><td rowspan="2">NI/NG vs. NI/G << NI/NG vs. I/NG; NI/NG vs. I/G; NI/G vs. I/NG; NI/G vs. I/NG
NI/NG vs. I/NG << NI/G vs. I/NG; NI/NG vs. I/G; NI/NG vs. I/NG</td></tr>
<tr><td>*t-test vs. 50%*</td><td colspan="4">ns</td><td colspan="4">***</td><td colspan="4">***</td><td colspan="4">****</td><td colspan="4">****</td><td colspan="4">ns</td><td>--</td></tr>
<tr><td rowspan="2">**RT**</td><td rowspan="2">*RM (2 x 4)*</td><td colspan="6">No Info / No Gap</td><td colspan="6">No Info / Gap</td><td colspan="6">Info / No Gap</td><td colspan="6">Info/ Gap</td><td>**</td><td>--</td></tr>
<tr><td colspan="3">Left
M = 0.54</td><td colspan="3">Right
M = 0.54</td><td colspan="3">Left
M = 0.55</td><td colspan="3">Right
M = 0.51</td><td colspan="3">Left
M = 0.57</td><td colspan="3">Right
M = 0.54</td><td colspan="3">Left
M = 0.57</td><td colspan="3">Right
M = 0.55</td><td>**</td><td>R << L</td></tr>
<tr><td rowspan="3"></td><td rowspan="3">*RM (6 x 2 x 2)*</td><td colspan="4">No info/no gap vs. No info/gap</td><td colspan="4">No info/no gap vs. Info/ No gap</td><td colspan="4">No info/no gap vs. Info/ gap</td><td colspan="4">No Info/gap vs. Info/ No gap</td><td colspan="4">No Info/gap vs. Info/No gap</td><td colspan="4">No info/no gap vs. Info/No gap</td><td>--</td><td>--</td></tr>
<tr><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td>**</td><td>R << L</td></tr>
<tr><td>P
0.67</td><td>N
0.71</td><td>P
0.66</td><td>N
0.69</td><td>P
0.67</td><td>N
0.75</td><td>P
0.68</td><td>N
0.70</td><td>P
0.66</td><td>N
0.72</td><td>P
0.67</td><td>N
0.68</td><td>P
0.68</td><td>N
0.71</td><td>P
0.66</td><td>N
0.66</td><td>P
0.66</td><td>N
0.75</td><td>P
0.65</td><td>N
0.69</td><td>P
0.70</td><td>N
0.71</td><td>P
0.70</td><td>N
0.70</td><td>*</td><td>NP << P</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">*RM (2 x 2)*</td><td colspan="12">Single</td><td colspan="12">Double</td><td>***</td><td>Single << Double</td></tr>
<tr><td colspan="6">Left
M = 0.55</td><td colspan="6">Right
M = 0.52</td><td colspan="6">Left
M = 0.68</td><td colspan="6">Right
M = 0.69</td><td>--</td><td>--</td></tr>
<tr><td rowspan="2">**MT**</td><td rowspan="2">*RM (2 x 4)*</td><td colspan="6">No Info / No Gap</td><td colspan="6">No Info / Gap</td><td colspan="6">Info / No Gap</td><td colspan="6">Info/ Gap</td><td>**</td><td>--</td></tr>
<tr><td colspan="3">Left
M = 0.63</td><td colspan="3">Right
M = 0.60</td><td colspan="3">Left
M = 0.63</td><td colspan="3">Right
M = 0.59</td><td colspan="3">Left
M = 0.64</td><td colspan="3">Right
M = 0.60</td><td colspan="3">Left
M = 0.62</td><td colspan="3">Right
M = 0.61</td><td>**</td><td>R << L</td></tr>
<tr><td rowspan="3"></td><td rowspan="3">*RM (6 x 2 x2)*</td><td colspan="4">No info/no gap vs. No info/gap</td><td colspan="4">No info/no gap vs. Info/ No gap</td><td colspan="4">No info/no gap vs. Info/ gap</td><td colspan="4">No Info/gap vs. Info/ No gap</td><td colspan="4">No Info/gap vs. Info/No gap</td><td colspan="4">No info/no gap vs. Info/No gap</td><td>--</td><td>--</td></tr>
<tr><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td>**</td><td>R << L</td></tr>
<tr><td>P
0.71</td><td>N
0.69</td><td>P
0.65</td><td>N
0.68</td><td>P
0.69</td><td>N
0.59</td><td>P
0.66</td><td>N
0.66</td><td>P
0.69</td><td>N
0.71</td><td>P
0.66</td><td>N
0.68</td><td>P
0.70</td><td>N
0.75</td><td>P
0.66</td><td>N
0.69</td><td>P
0.69</td><td>N
0.71</td><td>P
0.65</td><td>N
0.67</td><td>P
0.71</td><td>N
0.74</td><td>P
0.70</td><td>N
0.70</td><td>*</td><td>NP << P</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">*RM (2 x 4)*</td><td colspan="12">Single</td><td colspan="12">Double</td><td>***</td><td>Single << Double</td></tr>
<tr><td colspan="6">Left
M = 0.63</td><td colspan="6">Right
M = 0.60</td><td colspan="6">Left
M = 0.71</td><td colspan="6">Right
M = 0.70</td><td>--</td><td>--</td></tr>
<tr><td>**Reach Area**</td><td>*RM (1 x 4)*</td><td colspan="6">No Info / No Gap
Area = 207.43</td><td colspan="6">No Info / Gap
Area = 210.48</td><td colspan="6">Info / No Gap
Area = 204.06</td><td colspan="6">Info/ Gap
Area = 205.53</td><td>--</td><td>--</td></tr>
<tr><td></td><td>*RM (1 x 6)*</td><td colspan="4">No info/no gap vs. No info/gap
Area = 201.80</td><td colspan="4">No info/no gap vs. Info/ No gap
Area = 200.84</td><td colspan="4">No info/no gap vs. Info/ gap
Area = 212.18</td><td colspan="4">No Info/gap vs. Info/ No gap
Area = 201.65</td><td colspan="4">No Info/gap vs. Info/No gap
Area = 213.76</td><td colspan="4">No info/no gap vs. Info/No gap
Area = 187.20</td><td>--</td><td>--</td></tr>
<tr><td></td><td>*RM (1 x 2)*</td><td colspan="12">Single
Area = 206.87</td><td colspan="12">Double
Area = 202.91</td><td>***</td><td>Single << Double</td></tr>
<tr><td>**Subjective Report**</td><td>*RM (1 x 4)*</td><td colspan="6">No Info / No Gap
M = -22.3</td><td colspan="6">No Info / Gap
M = -20.37</td><td colspan="6">Info / No Gap
M = 5.70</td><td colspan="6">Info/ Gap
M = 5.50</td><td>***</td><td>I/G >> NI/G; NI/NG
I/NG >> NI/G; NI/NG</td></tr>
<tr><td></td><td>*t-test vs. 0%*</td><td colspan="6">***</td><td colspan="6">***</td><td colspan="6">ns</td><td colspan="6">ns</td><td>--</td><td>--</td></tr>
</table>

3.1.2) Reaction Time

As stated in the Data Analysis plan, 3 RM-ANOVAs were conducted on reaction time (RT) for Experiments 1 and 2. The first was a 2 x 4 (side of space x single target shape), RM-ANOVA to examine reaction time toward trials with only a single target on the screen. In Experiment 1, there was a main effect for shapes [$F(3,87) = 4.34$, $p < 0.05$] and side of space [$F(1,29) = 13.26$, $p < 0.01$] as seen in figure 3.2A and detailed in Table 1.0. Here, subjects reacted faster towards non-informative, high probability shapes. In addition, they reacted faster towards shapes on the right side of space. For Experiment 2, this 2 x 4 RM-ANOVA had no significant effects or interactions, suggesting fast reaction times in Experiment 1 are mostly driven by high probability shapes. The second test was a three-way, 6 x 2 x 2 RM-ANOVA (shape pairs x side of space x preferred choice) looking at reaction times on trials with two targets. For Experiment 1, there was a main effect for side of space [$F(1,23) = 11.60$, $p < 0.01$], and a main effect for preferred shapes [$F(1,23) = 5.19$, $p < 0.05$] as seen in figure 3.2 and found in Table 1.0. In Experiment 1, subjects reacted faster when responding to the right side in paired shapes, and they reacted faster towards shapes they preferred hitting. For Experiment 2, the 6 x 2 x 2 RM-ANOVA returned no significant main effects or interactions, furthering our speculation that reaction time is driven primarily by probability difference (which were held constant in Experiment 2). The third test was a 2 x 2 RM-ANOVA (single/double shapes x side of space) to compare reaction time across single and two target trials. In both Experiments 1 and 2, there was a main effect for the single/double factor [Experiment 1, $F(1,26) = 21.02$, $p < 0.0001$] [Experiment 2, [$F(1,26) = 87.60$, $p < 0.0001$] with double trials leading to longer reaction times. Additionally, there was no main effect for side of space in either Experiment 1 or Experiment 2 for reaction times in this third RMANOVA. Summarizing reaction time, there is a main effect

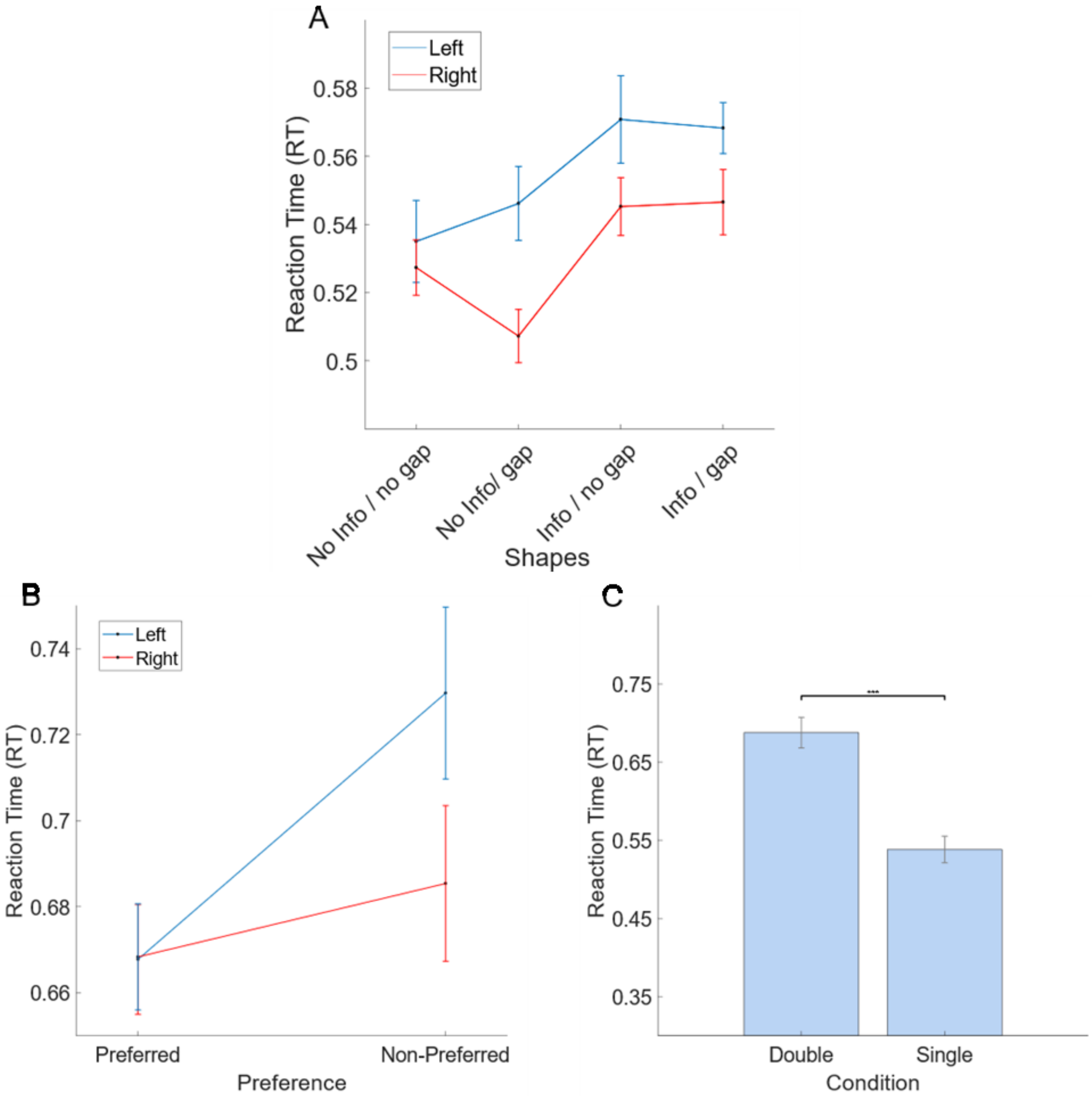

Figure 3.2) Reaction Time (RT) RM-ANOVA tests for Experiment 1. All error bars represent 95% CI for within subject's design. A) RM-ANOVA 2 x 4 (side of space x single target shape). Overall, subjects react faster to the non-informative, higher probability shapes, as well as right side shapes. B) RM-ANOVA 6 x 2 x 2 (paired condition x side of space x preferred choice). Overall, subjects react faster to preferred shapes, as well as shapes on the right side of space in paired conditions. C) RM-ANOVA 2 x 2 (single/double conditions x side of space). Here, subjects react faster to single target trials vs. double target. Asterisks indicates significance, refer to Table 1.0 for p-values.

for side of space in the first two RM-ANOVA of Experiment 1, where subjects react faster when selecting targets on the right. In addition, for Experiment 1, subjects react faster when selecting high probability shapes which mirrors their preference effect. This effect is not seen in Experiment 2, presumably because all shapes were given an equal probability of rewards. Lastly, subjects reacted faster to shapes where there was only one target on the screen as opposed to two, suggesting that the decision between two targets takes some time.

3.1.3) Movement Time

Movement times used the same set of analyses and reflected almost identical findings to reaction time in Experiments 1 and 2. The first 2 x 4 RM-ANOVA on single target trials (side of space x single target shape) returned a main effect for side of space in both Experiment 1 and Experiment 2 [Experiment 1, $F(1,29) = 24.17$, $p < 0.0001$] [Experiment 2, [$F(1,29) = 15.03$, $p < 0.001$] with faster movements to the right as seen in figures 3.3A and 3.3D and Table 1.0 and 2.0. The second 6 x 2 x 2 RM-ANOVA on two- target trials (paired shapes x side of space x preferred choice) returned a side of space main effect [$F(1,23) = 28.46$, $p < 0.0001$], with faster movements to the right, and a preferred choice main effect, with faster moments toward preferred options [$F(1,23) = 4.27$, $p < 0.05$] in Experiment 1 (see figures 3.3B and 3.3F at Table 1.0). For E2, this 6 x 2 x 2 RM-ANOVAS only showed a main effect for side of space [$F(1,23) = 37.30$, $p < 0.0001$], with faster movements to the right. This replicates the finding that high probability shapes are driving faster behavior in Experiment 1 but are less prevalent in Experiment 2 where targets are equiprobable. The third 2 x 2 RM-ANOVA compared single to two-target trials (single/double shapes x side of space) and returned a main effect for the single/double shapes in both Experiments 1 and 2 [Experiment 1, $F(1,26) = 111.00$, $p < 0.0001$] [Experiment 2, [$F(1,26) = 279.80$, $p < 0.0001$] where movements on two-target trials were slower. In addition, in Experiment 2, there was yet again a main effect for side of space [$F(1,26) = 24.46$, $p < 0.0001$] as detailed in Table 2.0 (see figures 3.3C for Experiment 1, and 3.3F for Experiment 2). As mentioned, movement times for Experiment 1 and Experiment 2 replicated the same patterns as reaction time. In both experiments, subjects moved faster towards shapes on the right side and single target shapes. In Experiment 1, subjects also moved faster towards high probability shapes.

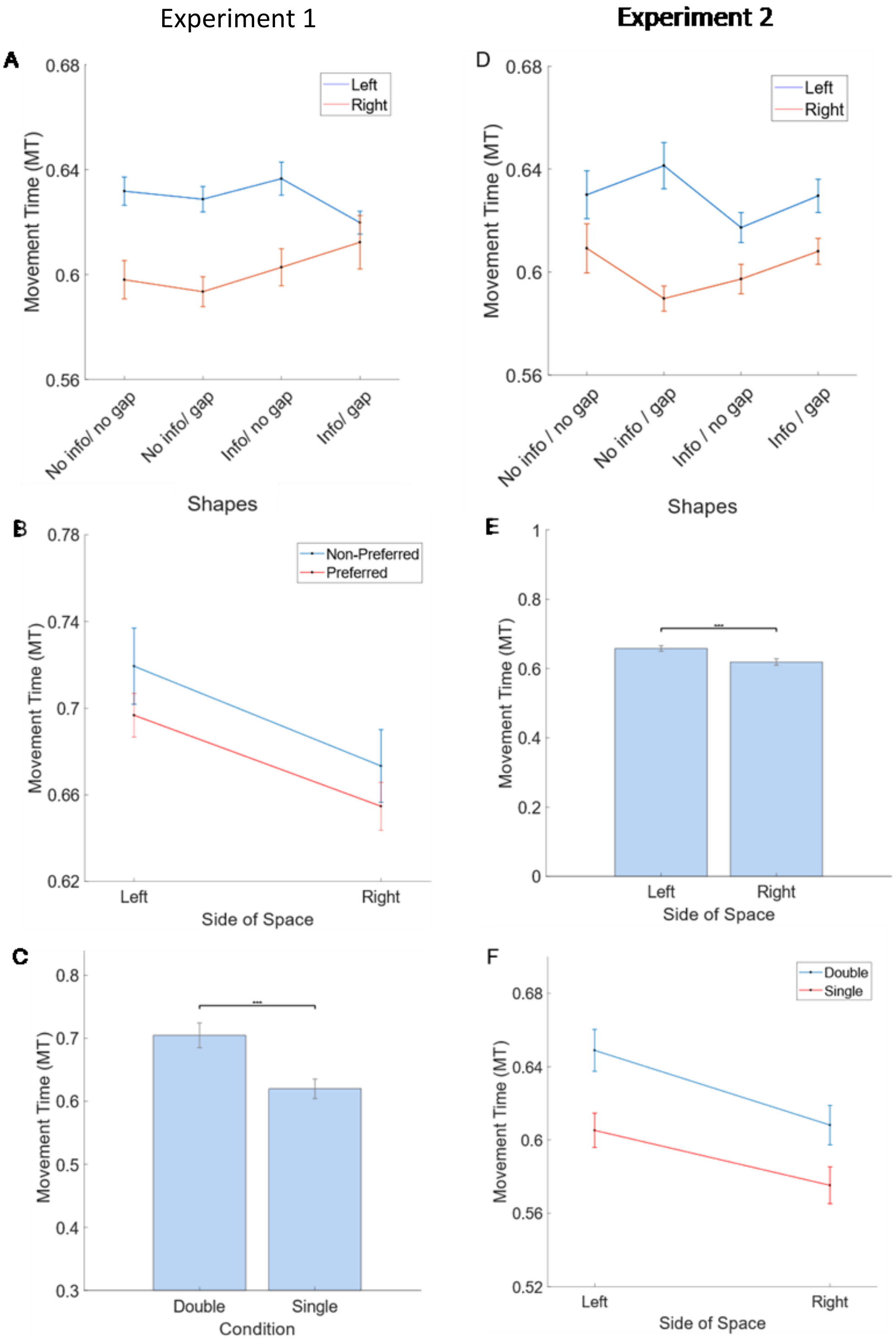

Figure 3.3) Movement Time RMANOVA results from Experiment 1 (A-C) and Experiment 2 (D-F). A and D) 2 x 4 (side of space x single target shape) RM-ANOVA. There is a main effect for side of space, showing subjects move faster to right side shapes. **B and E)** 6 x 2 x 2 RM-ANOVA on two-target trials (paired shapes x side of space x preferred choice) returned a side of space main effect, again showing subjects moving faster to right side shapes. **C and F)** 2 x 2 RM-ANOVA compared single to two-target trials (single/double shapes x side of space. Subjects were faster at moving toward single target shapes vs. paired shapes. For **F)** There is also a main effect for side of space, with subjects moving faster to shapes on the right side of space.

Table 2) Experiment 2 means and statistical tests

<table>
<tr><th>Measure</th><th>Test</th><th colspan="24">Condition</th><th>F</th><th>Pairwise</th></tr>
<tr><td rowspan="2">**Choice Preference**</td><td>*RM (1 x 6)*</td><td colspan="4">*No info/no gap* vs. No info/gap</td><td colspan="4">*No info/no gap* vs. Info/ No gap</td><td colspan="4">*No info/no gap* vs. Info/ gap
M = 53.77%</td><td colspan="4">*No Info/gap* vs. Info/ No gap
M = 45.50</td><td colspan="4">*No Info/gap* vs. Info/No gap
M = 50.51%</td><td colspan="4">*No info/no gap* vs. Info/No gap</td><td>ns</td><td rowspan="2">--</td></tr>
<tr><td>*t-test vs. 50%*</td><td colspan="4">ns</td><td colspan="4">ns</td><td colspan="4">ns</td><td colspan="4">ns</td><td colspan="4">ns</td><td colspan="4">ns</td><td>--</td></tr>
<tr><td rowspan="2">**RT**</td><td rowspan="2">*RM (2 x 4)*</td><td colspan="6">No Info / No Gap</td><td colspan="6">No Info / Gap</td><td colspan="6">Info / No Gap</td><td colspan="6">Info/ Gap</td><td>ns</td><td>--</td></tr>
<tr><td colspan="3">Left
M = 0.54</td><td colspan="3">Right
M = 0.51</td><td colspan="3">Left
M = 0.51</td><td colspan="3">Right
M = 0.50</td><td colspan="3">Left
M = 0.50</td><td colspan="3">Right
M = 0.51</td><td colspan="3">Left
M = 0.51</td><td colspan="3">Right
M = 0.52</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="3"></td><td rowspan="3">*RM (6 x 2 x2)*</td><td colspan="4">No info/no gap vs. No info/gap</td><td colspan="4">No info/no gap vs. Info/ No gap</td><td colspan="4">No info/no gap vs. Info/ gap</td><td colspan="4">No Info/gap vs. Info/ No gap</td><td colspan="4">No Info/gap vs. Info/No gap</td><td colspan="4">No info/no gap vs. Info/No gap</td><td>ns</td><td>--</td></tr>
<tr><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td>ns</td><td>--</td></tr>
<tr><td>P
0.63</td><td>N
0.64</td><td>P
0.65</td><td>N
0.64</td><td>P
0.63</td><td>N
0.70</td><td>P
0.63</td><td>N
0.64</td><td>P
0.63</td><td>N
0.66</td><td>P
0.63</td><td>N
0.63</td><td>P
0.64</td><td>N
0.62</td><td>P
0.63</td><td>N
0.65</td><td>P
0.63</td><td>N
0.66</td><td>P
0.62</td><td>N
0.64</td><td>P
0.63</td><td>N
0.65</td><td>P
0.62</td><td>N
0.66</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">*RM (2 x 2)*</td><td colspan="12">Single</td><td colspan="12">Double</td><td>***</td><td>Single << Double</td></tr>
<tr><td colspan="6">Left
M = 0.51</td><td colspan="6">Right
M = 0.50</td><td colspan="6">Left
M = 0.64</td><td colspan="6">Right
M = 0.62</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2">**MT**</td><td rowspan="2">*RM (2 x 4)*</td><td colspan="6">No Info / No Gap</td><td colspan="6">No Info / Gap</td><td colspan="6">Info / No Gap</td><td colspan="6">Info/ Gap</td><td>ns</td><td>--</td></tr>
<tr><td colspan="3">Left
M = 0.63</td><td colspan="3">Right
M = 0.61</td><td colspan="3">Left
M = 0.64</td><td colspan="3">Right
M = 0.59</td><td colspan="3">Left
M = 0.62</td><td colspan="3">Right
M = 0.60</td><td colspan="3">Left
M = 0.63</td><td colspan="3">Right
M = 0.60</td><td>**</td><td>R << L</td></tr>
<tr><td rowspan="3"></td><td rowspan="3">*RM (6 x 2 x2)*</td><td colspan="4">No info/no gap vs. No info/gap</td><td colspan="4">No info/no gap vs. Info/ No gap</td><td colspan="4">No info/no gap vs. Info/ gap</td><td colspan="4">No Info/gap vs. Info/ No gap</td><td colspan="4">No Info/gap vs. Info/No gap</td><td colspan="4">No info/no gap vs. Info/No gap</td><td>ns</td><td>--</td></tr>
<tr><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td>***</td><td>R << L</td></tr>
<tr><td>P
0.66</td><td>N
0.67</td><td>P
0.65</td><td>N
0.62</td><td>P
0.65</td><td>N
0.65</td><td>P
0.62</td><td>N
0.64</td><td>P
0.65</td><td>N
0.65</td><td>P
0.62</td><td>N
0.63</td><td>P
0.64</td><td>N
0.68</td><td>P
0.62</td><td>N
0.63</td><td>P
0.66</td><td>N
0.66</td><td>P
0.64</td><td>N
0.64</td><td>P
0.65</td><td>N
0.68</td><td>P
0.62</td><td>N
0.61</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">*RM (2 x 4)*</td><td colspan="12">Single</td><td colspan="12">Double</td><td>***</td><td>Single << Double</td></tr>
<tr><td colspan="6">Left
M = 0.60</td><td colspan="6">Right
M = 0.58</td><td colspan="6">Left
M = 0.64</td><td colspan="6">Right
M = 0.61</td><td>**</td><td>R << L</td></tr>
<tr><td>**Reach Area**</td><td>*RM (1 x 3)*</td><td colspan="6">No Info / No Gap
Area = 276.89</td><td colspan="6">No Info / Gap
Area = 280.27</td><td colspan="6">Info / No Gap
Area = 293.80</td><td colspan="6">Info/ Gap
Area = 276.57</td><td>ns</td><td>--</td></tr>
<tr><td></td><td>*RM (1 x 3)*</td><td colspan="4">No info/no gap vs. No info/gap
Area = 222.99</td><td colspan="4">No info/no gap vs. Info/ No gap
Area = 232.33</td><td colspan="4">No info/no gap vs. Info/ gap
Area = 237.14</td><td colspan="4">No Info/gap vs. Info/ No gap
Area = 232.15</td><td colspan="4">No Info/gap vs. Info/No gap
Area = 213.12</td><td colspan="4">No info/no gap vs. Info/No gap
Area = 224.65</td><td>ns</td><td>--</td></tr>
<tr><td></td><td>*RM (1 x 2)*</td><td colspan="12">Single
Area = 281.89</td><td colspan="12">Double
Area = 227.06</td><td>***</td><td>Single << Double</td></tr>
<tr><td>**Subjective Report**</td><td>*RM (2 x 4)*</td><td colspan="6">No Info / No Gap
M = -4.08</td><td colspan="6">No Info / Gap
M = -10.67</td><td colspan="6">Info / No Gap
M = -5.58</td><td colspan="6">Info/ Gap
M = -9.00</td><td>ns</td><td>--</td></tr>
<tr><td></td><td>*t-test vs. 0%*</td><td colspan="6">Ns</td><td colspan="6">**</td><td colspan="6">ns</td><td colspan="6">ns</td><td>--</td><td>--</td></tr>
</table>

3.1.4) Reach Area

For reach area, we conducted three, one-way ANOVAs to examine reach trajectories for Experiments 1 and 2. The first RM-ANOVA (1 x 4) examined all 4 single target shapes, counterbalanced for each side to calculate reach area. In both Experiments 1 and 2, there was a non-significant p-value [Experiment 1, F (3,87) = 0.29, $p > 0.05$] [Experiment 2, [F (3,87) = 0.25, $p > 0.05$], suggesting there is no difference in reach areas when reaching toward each shape individually. The second ANOVA was a 1 x 6, with the paired target shapes representing the 6 levels, and the reach area being calculated for the preferred shape on the left and right side in each shape pair. Again, for both Experiments 1 and 2, there was no significant effect for any paired shapes [Experiment 1, F (5,145) = 1.70, $p > 0.05$] [Experiment 2, F (5,140) = 1.68, $p > 0.05$]. The final 1 x 2 ANOVA comparing single to shape pair trials returned a significant effect for the single/double factors for both Experiments 1 and 2 [Experiment 1, F (1,29) = 54.19, $p < 0.0001$] [Experiment 2, F (1,29) = 22.96, $p < 0.0001$] with slower movements on paired shape trials. This suggests that subjects were reaching straighter towards single targets on a screen, while paired targets garnered more curvature in their reaches, in line with our hypothesis that decision difficulty, which prolongs reaction time, is also manifest in the movements (Chapman et al.,2015; Chapman, et al., 2010; Gallivan & Chapman, 2014; Truong, Chapman, Huang, & Enns, 2013).

3.1.5) Subjective Reports

For subjective reports, we ran a cluster of one-sample t-tests for subjective reported values vs. actual values in Experiments 1 and 2. In Experiment 1, the non-informative, high probability shape was significantly undervalued by participants [t (29) = -6.20, $p < 0.0001$], as was the non-informative, delay shape [t (29) = -4.76, $p < 0.0001$]. For Experiment 2, only the non-informative, gap shape (t (29) = -2.94, p < 0.01) was significantly undervalued.

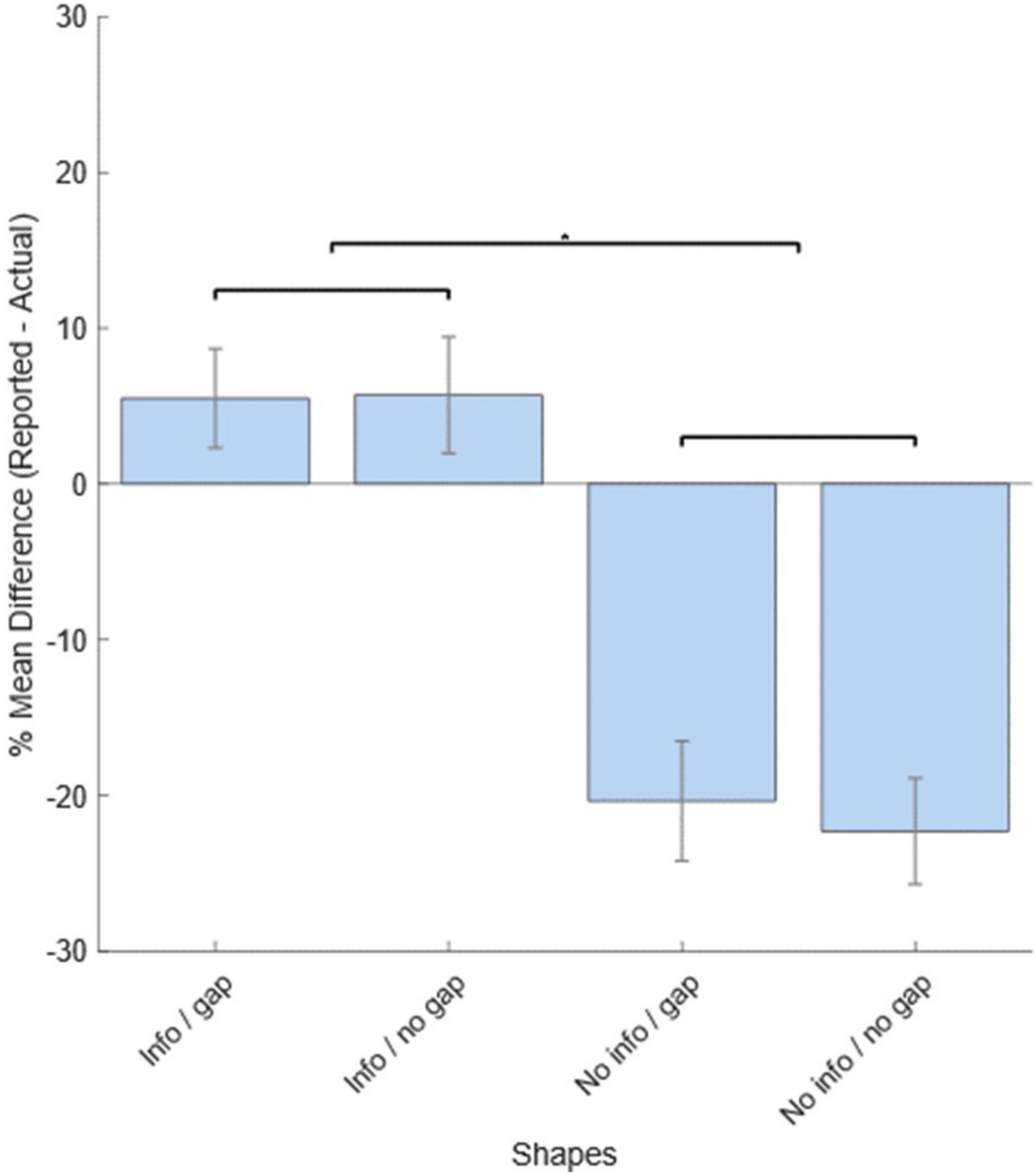

Figure 3.4) Subjective reports for Experiment 1. Mean % differences were calculated by subtracting reported values from actual values for each given shape. Subjects overvalued the high probability, non-informative shapes, while they significantly undervalued low probability, informative shapes. Asterisks indicates significance (* $p < 0.05$).

It is difficult to draw any firm conclusions from this data, since reports, especially in Experiment 1, were generally inaccurate. However, where this is a pattern, it appears that information increased report accuracy. As mentioned, we conducted a one-way, RM-ANOVA between subjective preferences for all 4 shapes in Experiments 1 and 2. Only Experiment 1 returned a significant p-value [$F(3,87) = 14.39$, $p < 0.0001$] and Experiment 2 did not return a significant p-value [$F(3,87) = 0.84$, $p > 0.05$]. Among the shapes in Experiment 1, the difference between the two informative shapes were not significantly different from each other. The difference between the two uninformative shapes were also not significantly different from each other. However, the informative shapes were significantly different from the non-informative ones (see figure 3.4 and Table 1.0 for full details). While informative shapes were approximately overvalued by 5%, non-informative shapes were undervalued by nearly 21% This suggests that subjects reported a clear difference between how they were being paid off by informative shapes vs. non-informative shapes. Ironically, they felt the higher probability shapes were rewarding less than their actual pay off and estimated the lower probability shapes were rewarding more than their actual pay off. Overall, they estimated that lower probability shapes paid off points 40% of the time, and high probability shapes paid off 45% of the time. This trend suggests that perhaps participants were somewhat disinterested in the task and just estimated all shapes as being about the same.

3.2) Experiment 3 & Experiment 4

3.2.1) Choice Preference

For Experiments 3 and 4, one sample t-tests were conducted for all 3 paired shapes to examine if choice preferences were significantly different from chance (50%, significant if $p<0.05/3$). In Experiment 3, all three shape pairs (neutral vs. good, neutral vs. bad, good vs. bad) were different from 50% as seen in figure 3.5A. For the neutral vs. good information shape pair, subjects preferred good news 85% of the time [$t (19) = -7.43$, $p < 0.0001$]. For the neutral vs. bad information shape pair, subjects preferred neutral information 86% of the time [$t (19) = 15.76$, $p < 0.0001$]. In the good vs. bad information shape pair, subjects preferred good news 92% of the time [$t (19) = 28.72$, $p < 0.0001$]. For Experiment 4, only 2 out of the 3 t-tests came back significant. In the neutral vs. good information shape pair, subjects preferred the good news shape 66% of the time [$t (24) = -3.90$, $p < 0.001$]. In the good vs. bad information shape pair, subjects preferred the good news shape 69% of the time [$t (24) = 5.18$, $p < 0.0001$]. Finally, while failing to meet our stringent statistical significance, subjects demonstrated a preference for neutral over bad information [$t (24) = 2.38$, $p = 0.02$]. In both experiments, the one-way RM-ANOVA looking for differences in choice preferences for each shape pair were not significant [Experiment 3, $F (2,38) = 1.70$, $p > 0.05$] [Experiment 4, [$F (2,48) = 2.52$, $p > 0.05$]. In general, however, in Experiments 3 and 4 subjects favored good over neutral or bad news, and neutral over bad news, with the strongest numerical preference for good news.

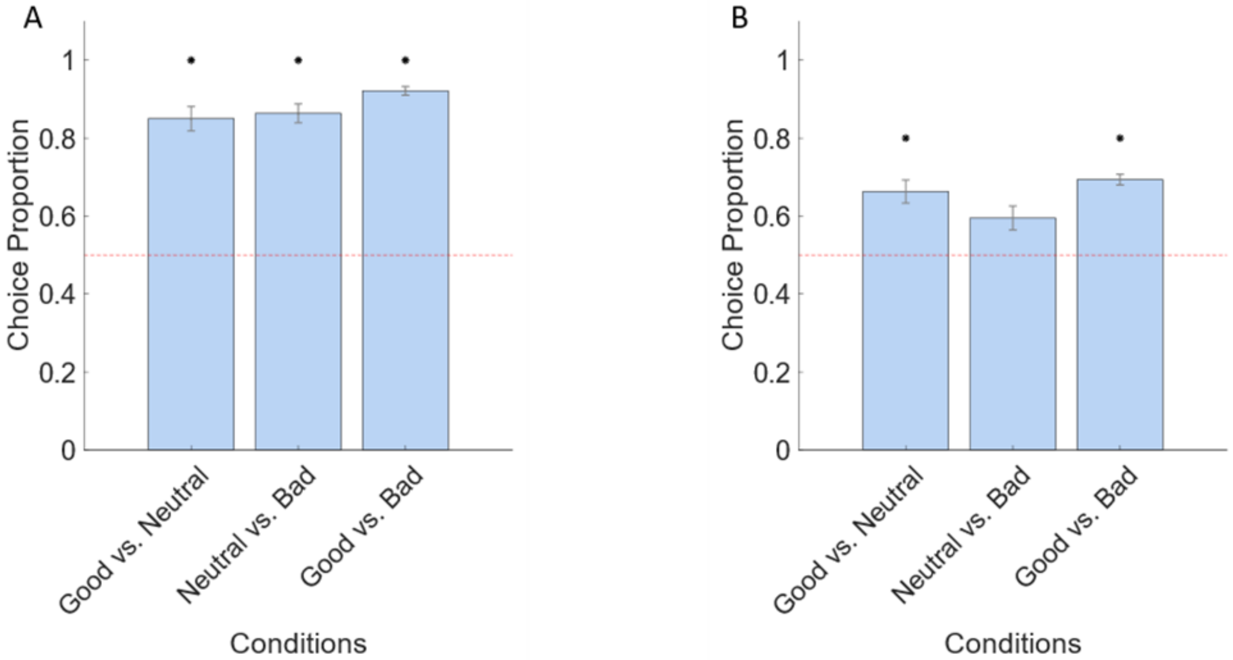

Figure 3.5) Choice preferences for Experiment 3 (A) and Experiment 4 (B). All shape pairs are significantly different from 50% with good news shapes garnering the biggest preference. Neutral vs. Bad was significant by traditional $p < 0.05$ standards ($p < 0.02$) but did not reach the Bonferroni correction criteria ($p < 0.0166$). Loftus and Masson (1994) within-subject error bars and represent 95% confidence intervals (CIs).

3.2.2) Reaction Time

The same 3 RM-ANOVAs for Experiments 3 and 4 for reaction time were derived from Experiments 1 and 2. The first test was a 2 x 3 (side of space x single target shape) factor RM-ANOVA for single target shapes. For Experiment 3, there was a main effect for shapes [$F(2,38) = 5.26$, $p < 0.05$], and side of space [$F(1,19) = 4.93$, $p < 0.05$] as seen in figure 3.6 and detailed in Table 3.0. On average, subjects were faster reacting to good news shapes over neutral or bad news shapes. In addition, subjects reacted faster to shapes on the right side of space. For Experiment 4, there was no significant effect for condition, or side of space for reaction time. The second test was a RM-ANOVA, with a 3 x 2 x 2 factor design (shape pairs x preferred shapes x side of space). In both Experiments 3 and 4, there was no significant effect for this RM-ANOVA as detailed in Table 3.0 and 4.0. The last test was a RM-ANOVA, with a 2 x 2 factor design (single/double shapes x side of space), which was testing for differences between one and two target trials. In both Experiments 3 and 4, there was a main effect for the single/double factor [E3, $F (1,11) = 13.82$, $p < 0.01$] [E4, [$F (1,24) = 19.98$, $p < 0.001$] with longer RTs when the participants were choosing between two shapes. Summarizing reaction time, subjects reacted faster towards single target compared to double target shape pairs in both Experiments 3 and 4. In single target trials for Experiment 3, subjects reacted faster to good news over neutral or bad news shapes, while also reacting faster to shapes on the right side. We take this as partial evidence for people treating the good news in Experiment 3 like a primary reward and is thus in line with our Experiment 1 results. This justifies the need to examine Experiment 4, and here it appears as if RTs in Experiment 4 did not differentiate between news shape pairs, suggesting we partially succeeded in having the information be separated from the reward.

Table 3.0) Experiment 3 means and statistical results

Measure	Test/ Factors	Condition												F	Pairwise
Choice Preference	*RM (1 x 3)*	*Good news* vs. Neutral News *M = 85.00%*				*Neutral News* vs. Bad News *M = 86.40%*				*Good News* vs, Bad News *M = 53.77%*				ns	--
	t-test vs. 50%	*				*				*				--	
RT	*RM (2 x 4)*	Neutral News				Good News				Bad News				*	Good < Bad
		Left M = 0.39		Right M = 0.36		Left M = 0.36		Right M = 0.35		Left M = 0.37		Right M = 0.36		*	R < L
	RM (3 x 2 x 2)	Good News vs, Neutral News				Neutral News vs. Bad News				Good News vs. Bad News				ns	--
		Left		Right		Left		Right		Left		Right		ns	--
		P 0.39	N 0.41	P 0.37	N 0.42	P 0.39	N 0.41	P 0.39	N 0.41	P 0.39	N 0.40	P 0.38	N 0.41	ns	--
	RM (2 x 2)	Single						Double						***	Single << Double
		Left M = 0.38			Right M = 0.38			Left M = 0.42			Right M = 0.42			ns	--
MT	*RM (2 x 2)*	Neutral News				Good News				Bad News				ns	--
		Left M = 0.52		Right M = 0.48		Left M = 0.52		Right M = 0.49		Left M = 0.52		Right M = 0.48		**	R << L
	RM (3 x 2 x 2)	Good News vs, Neutral News				Neutral News vs. Bad News				Good News vs. Bad News				ns	--
		Left		Right		Left		Right		Left		Right		**	R << L
		P 0.54	N 0.55	P 0.52	N 0.52	P 0.56	N 0.58	P 0.54	N 0.53	P 0.54	N 0.52	P 0.52	N 0.54	ns	--
	RM (2 x 2)	Single						Double						--	--
		Left M = 0.50			Right M = 0.48			Left M = 0.55			Right M = 0,51			**	R << L
Reach Area	*RM (1 x 3)*	Neutral News Area = 314.06				Good News Area = 313.54				Bad News Area = 306.74				ns	--
	RM (1 x 3)	Good News vs. Neutral News Area = 259.80				Neutral News vs. Bad News Area = 200.09				Good News vs. Bad News Area = 275.00				***	G vs. N > N vs. B N vs. B << G vs. B
	RM (1 x 2)	Single Area = 311.45						Double Area = 244.97						***	Single >> Double
Subjective Report	*RM (2 x 2)*	Neutral News				Good News				Bad News				**	--
**Interaction Shape x Pre-post*	**POST**	M = 4.25				M = 10.50				M = -24.50				***	Good >> Bad Neutral >> Bad
	PRE	M = -0.50				M = 1.00				M = -10.50				ns	
	t-test vs. 0%	ns		ns		ns		ns		ns		**		--	--

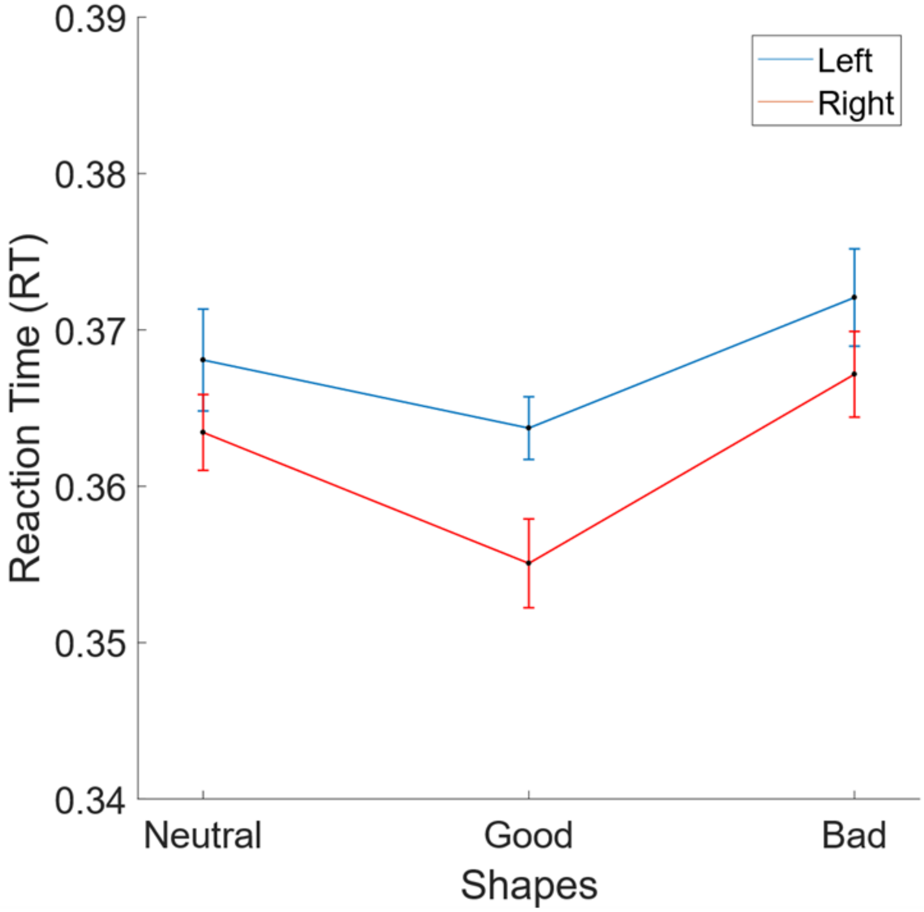

Figure 3.6) RM-ANOVA 2 x 3 (side of space x single target shape) of Reaction Time for Experiment 3. Subjects reacted faster towards good news shapes in the single target conditions. Subjects also reacted faster towards shapes on the right side of space.

3.2.3) Movement Time

For movement time, we ran the exact same statistical tests as reaction time. The first test was a 2 x 3 (single target vs. side of space) RM-ANOVA on single target trials. For both Experiments 3 and 4, there was only a main effect on side of space [Experiment 3, F (2,38) = 14.74, $p < 0.01$] [Experiment 4, F (2,48) = 41.68, $p < 0.0001$] (figure 3.7A & 3.8A) with subjects moving faster towards shapes on the right side. The second test was the 3 x 2 x 2 (shape pair x side of space x preferred) RM-ANOVA on two-target trials. For Experiment 3, there was only a main effect for side of space [F (1,10) = 19.09, $p < 0.01$] (figure 3.8B) showing faster

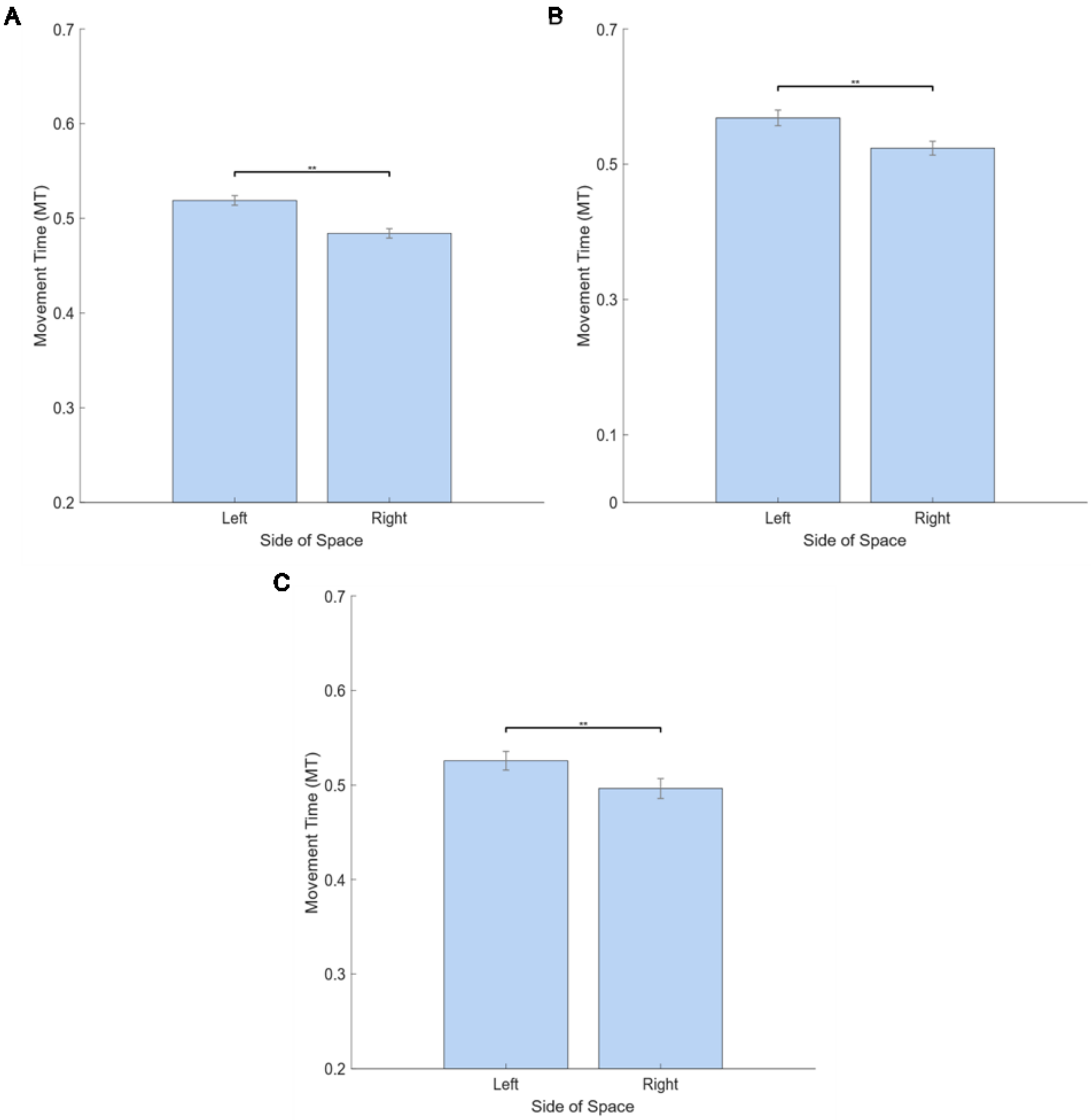

Figure 3.7) Movement Time results for Experiment 3. A) 2 x 3 (single target x side of space) RM-ANOVA on single target trials. Subjects moved faster to right target shapes vs. left. B) 6 x 2 x 2 (shape pair x side of space x preferred) RM-ANOVA on shape pair trials. Again, subjects move faster to right side shapes in shape pair trials. C) 2 x 2 (single/double shapes x side of space) RM-ANOVA revealed that subjects only move faster to shapes on the right side of space, regardless of whether it's a single or paired shape trial. Asterisks indicates significance ($p < 0.01$).**

movements towards shapes on the right side of space. For Experiment 4, there was a main effect for side of space [F (1,20) = 19.67, $p < 0.001$] and a 3-way interaction effect between side of space, shape pair and preferred shapes [F (2,40) = 4.13, $p < 0.05$]. To further investigate this interaction, we conducted two, 3 x 2 (shape pair x side of space) RM-ANOVA while holding the ‘preferred’ and “non-preferred” factors constant across shape pairs. For the first 3 x 2 RM-ANOVA on trials where participants chose preferred shapes across all shape pairs, we saw a main effect for side of space [F (1,24) = 14.83, $p < 0.001$]. Subjects were faster moving towards targets on the right side compared to the left. The second 3 x 2 RM-ANOVA held the non-preferred shapes constant. Here, we saw a main effect for side of space [F (1,24) = 12.12, $p < 0.01$] and an interaction effect between shape pair and side of space [F (2,48) = 3.22, $p < 0.05$]. The interaction effect occurred at the neutral vs. bad shape pair, where the right shape had a much faster movement time compared to the left as seen in figure 3.8C & D. To follow this up, we ran two, one-way ANOVAs for shape pairs in the non-preferred condition, while holding the left side constant, and then the right side to examine the simple main effects. For the first ANOVA (1 x 3), holding the left side constant with non-preferred shapes, there is no main effect for shape pairs [F (2,48) = 1.55, $p > 0.05$]. For the ANOVA holding the right-side constant (1 x 3), there is also no main effect [F (2,48) = 2.01, $p > 0.05$]. It appeared shape pairs with bad news drove this interaction effect. For non-preferred shapes where bad news was involved in a given shape pair, subjects moved faster to right side, non-preferred shape. For the good vs. neutral shape pair, no such side of space bias was present. Overall, subjects seemingly moved faster to shape pairs that were valanced in nature (good or bad), but shape pairs involving neutral news saw little or no difference. The last RM-ANOVA was a 2 x 2 comparing single to two- target trials (single/double shapes x side of space). For both Experiments 3 and 4, there was a main effect for side of space [Experiment 3, F (1,11) = 14.72, $p < 0.01$] [Experiment 4, [F (1,24) = 46.80, $p < 0.0001$]. For Experiment 4, there was also a main effect for the single/double factor [F (1,24) = 8.97, $p < 0.01$]. Subjects moved faster towards right targets in both experiments. But only in Experiment 4, subjects moved faster toward single target shapes vs. paired target shapes (see figure 3.8B).

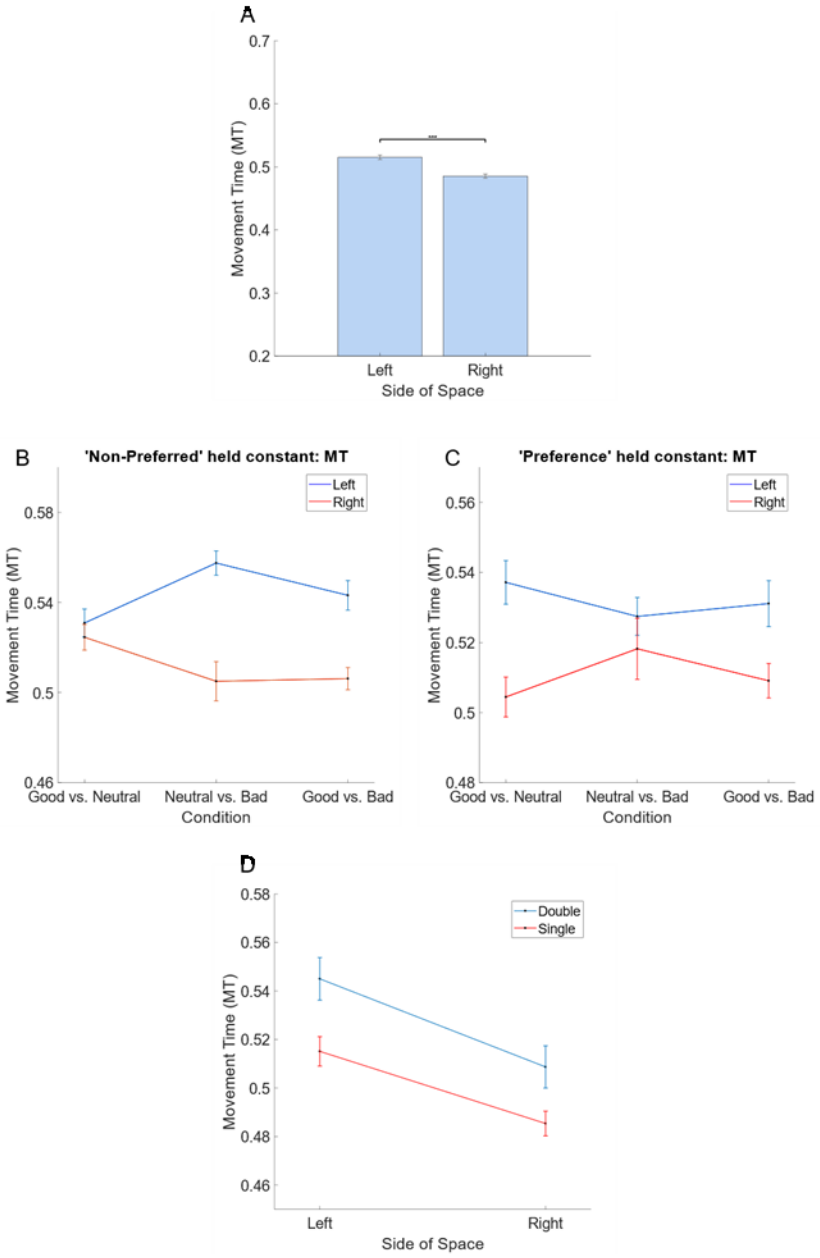

Figure 3.8) Movement Time ANOVA results for E4. A) 2 x 3 (single target x side of space) RM-ANOVA returned a significant main effect for side of space. B and C) The follow up 2-way RM-ANOVAS from the 6 x 2 x 2 (shape pair x side of space x preferred) RM-ANOVA. B) Non-preferred shapes held constant, and showed a main effect for side of space, and an interaction effect between shape pairs and side of space. C) Preferred shapes held constant and showed a main effect for side of space, with subjects moving faster toward right shapes. D) 2 x 2 (single/double shapes x side of space) RM-ANOVA shows that subjects move faster to shapes on the right side of space and single target trials. Asterisks indicates significance (* p < 0.0001).**

3.2.4) Reach Area

Our first test was a one way, RM-ANOVA for single target shapes, which had 3 levels, counterbalanced for side of space. For both Experiments 3 and 4, there was no significant difference between reach areas for any single shapes [Experiment 3, F (2,38) = 1.95, $p > 0.05$] [Experiment 4, [F (2,48) = 0.21, $p > 0.05$]. Secondly, we ran a one way, RM-ANOVA on the average reach areas of paired target shapes, which had 3 levels, when subjects opted for their preferred shapes. For Experiment 3, figure 3.9A illustrates the reach areas of all 3 shape pairs. There was a main effect between these shape pairs [F (2,38) = 17.96, $p < 0.001$]. Pairwise comparisons revealed that any time participants reached for a good news shape (good news vs neutral, good news vs bad news) the moved straighter than when they chose neutral over bad-news (see figures 3.9A and 3.10 and Table 3.0 for details). Thus, based on these reach areas, the neutral vs. bad news shape pair was the most difficult decision for subjects, while the good vs. bad news shape pair was considered the easiest decision. The same RM-ANOVA for Experiment 4 was not found to be significant [F (2,48) = 1.05, $p > 0.05$], but a similar pattern for good-news reaches to be straighter was numerically observed (see figure 3.9B). A third one-way RM-ANOVA was done on single target reach areas (counterbalanced for side of space) and paired targets. In both Experiments 3 and 4, we see main effect [E3, F (1,11) = 51.68, $p < 0.0001$] [E4, F (1,24) = 46.61, $p < 0.0001$] where subjects moved straighter towards single targets than when moving to decide between two targets.

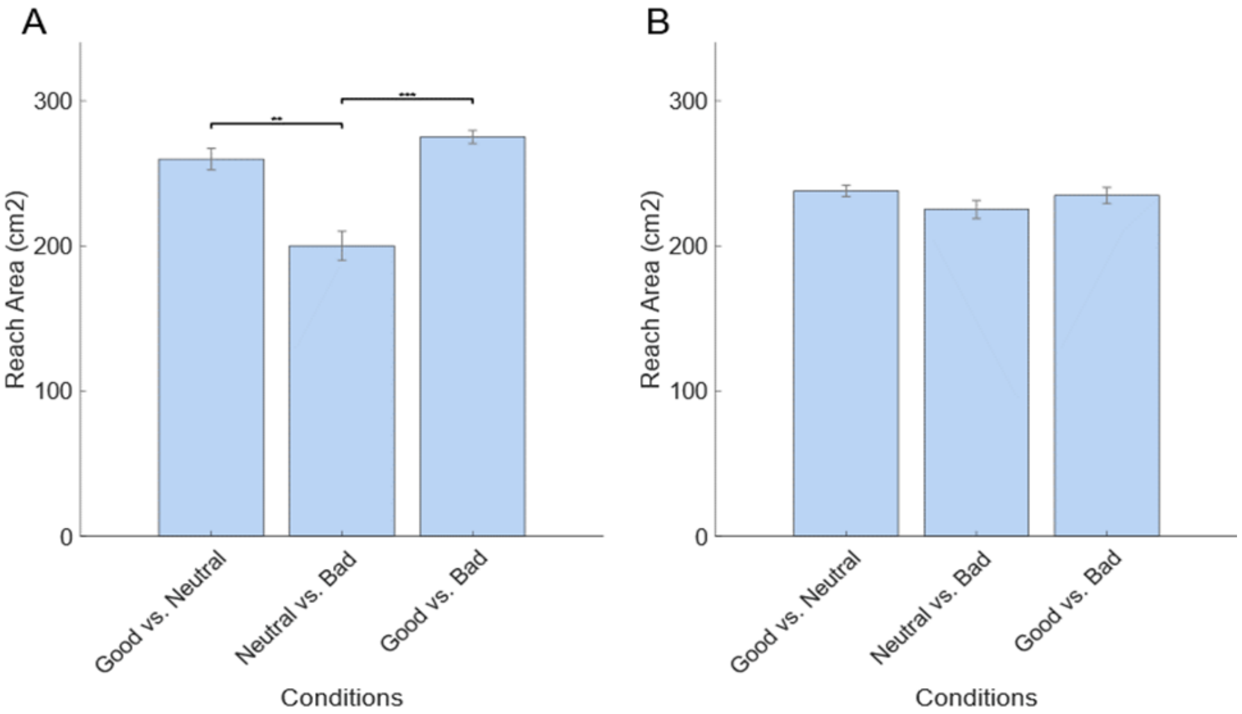

Figure 3.9) Reach Area (cm^2) for paired conditions in E3 and E4. **A)** Reach area for E3 indicates a much bigger area for conditions with good news contained, suggesting that motor decisions with those shapes are easier. The neutral vs. bad conditions indicates the hardest motor decision out of the three conditions. Asterisks indicates significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$). **B)** Reach area for E4 reveals no statistically significance among the three conditions. However, a similar trend is seen compared to E3. The neutral vs. bad condition was also the hardest motor decision in E4. Details in Table 3.0 and 4.0.

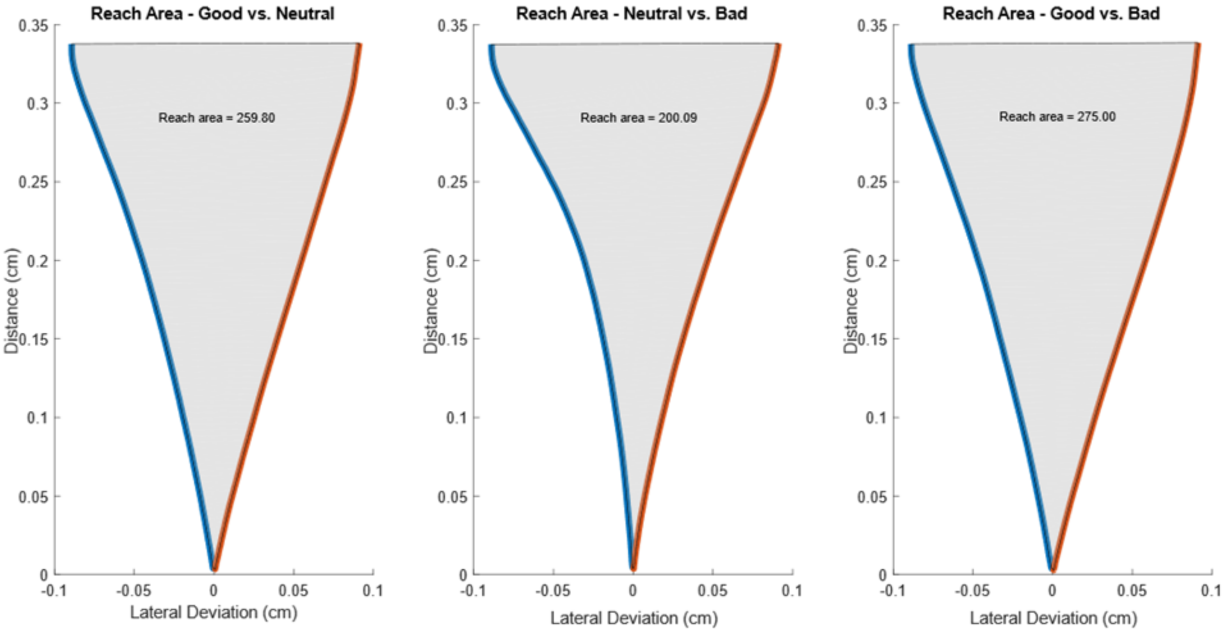

Figure 3.10) Reach trajectories (cm) for paired conditions in E3. Left Panel represents the good vs. neutral shape pair. Middle panel represents the neutral vs. bad shape pair. Right panel represents the good vs. bad shape pair. The largest reach area resides within the good vs. bad shape pair, and the lowest is the neutral vs. bad news shape pair.

3.2.5) Subjective Reports

We calculated subjective report scores in the same manner as Experiments 1 and 2 except in Experiments 3 and 4 we collected these reports both before and after the experimental trials. For Experiment 3, we conducted 6 one sample T-tests (3 shapes x pre and post questionnaire). Only the post-experiment, bad news shape returned a significant p-value [t (19) = -7.46, p < 0.0001] suggesting that reports were significantly different from the actual value. In Experiment 4, the pre-experiment neutral shape returned a significant p-value [t (24) = -3.17, p < 0.005] being undervalued by 15%. The pre-experiment good news shape was overvalued by 7.8% [t (24) = 2.14, p < 0.05]. Lastly, the post-experiment bad news shape was undervalued by 12% [t (24) = -3.15, p < 0.005]. We then conducted RM-ANOVAs with two factors (shape x pre-post) for both Experiments 3 and 4. In both experiments, there was a main effect for shape pair

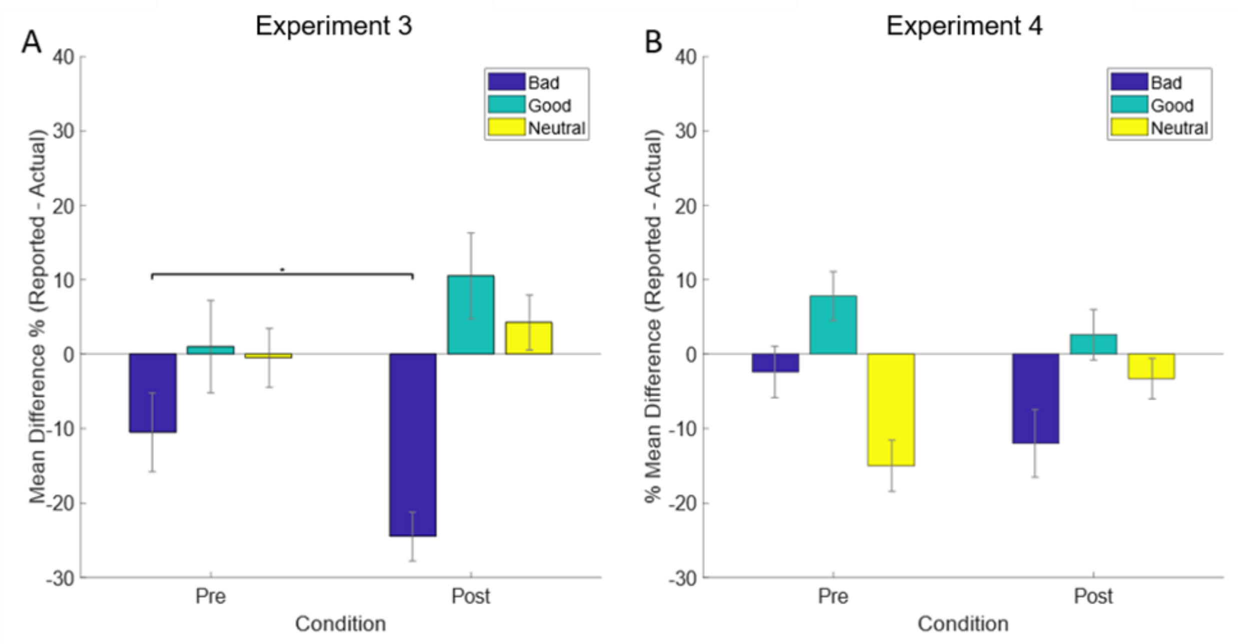

Figure 3.11) Subjective report results from Experiments 3 and 4 . A) This represents the 2 x 3 (shape x pre-post questionnaire) RM-ANOVA for Experiment 3. Here, there was a main effect for shape pair, and an interaction effect showing the difference in bad news from pre-post. B) This emulates the same statistical test, but for Experiment 4. Here, there is also a main effect for shape pairs, and an interaction effect between shape pairs and pre-post questionnaire status.

[Experiment 3, F (2,38) = 8.85, $p < 0.01$] [Experiment 4, F (2,48) = 6.70, $p < 0.01$] and an interaction effect [Experiment 3, F (2,38) = 5.60 $p < 0.05$] [Experiment 4, F (2,48) = 4.58, $p < 0.05$] as seen in figure 3.11. Post-hoc comparisons examined, for each shape, how their subjective value changed from Pre to Post. For Experiment 3, the bad news shape saw a significant decrease in reported reward value from pre to post (-10% to -25%). Conversely, good and neutral shapes increased in reported reward value from pre to post, but these increases were not statistically significant. In Experiment 4, while none of the changes from pre to post reached significance their subjective reports became more accurate by the end of the experiment for good and neutral shapes but became more inaccurate and lower for bad news shapes. To summarize, in Experiment 3, subjects felt they were rewarded more for good and neutral news shapes in their post-experiment questionnaire. At the same time, they reported that bad news was not rewarding, and felt it got worse from pre to post experiment. In Experiment 4, subjects were undervaluing bad and neutral news in the pre-experiment question, but only refined neutral news in the post-experiment, leaving bad news to be undervalued. Good news was overvalued in the pre-experiment questionnaire, but more accurately valued in the post-experiment. Taken together, this indicates subjects seemed to hone in on probability contingencies in Experiment 4 by subjectively reporting that they were being paid off approximately 50% of the time. However, the exception to this trend is the bad news shape in Experiment 4, where subjects undervalued bad news in the post questionnaire compared to the pre-questionnaire, which may reflect evidence of loss aversion.

Table 4.0) Experiment 4 means and statistical results

<table>
<tr><th>Measure</th><th>Test</th><th colspan="12">Condition</th><th>F</th><th>Pairwise</th></tr>
<tr><td rowspan="2">Choice Preference</td><td><i>RM
(1 x 3)</i></td><td colspan="4"><i>Good news</i> vs. Neutral News
<i>M = 66.28</i></td><td colspan="4"><i>Neutral News</i> vs. Bad News
<i>M = 59.50%</i></td><td colspan="4"><i>Good News</i> vs, Bad News
<i>M = 69.35%</i></td><td>ns</td><td rowspan="2">--</td></tr>
<tr><td><i>t-test vs. 50%</i></td><td colspan="4">*</td><td colspan="4">ns</td><td colspan="4">*</td><td>--</td></tr>
<tr><td rowspan="2">RT</td><td rowspan="2"><i>RM
(2 x 4)</i></td><td colspan="4">Neutral News</td><td colspan="4">Good News</td><td colspan="4">Bad News</td><td>*</td><td>Good < Bad</td></tr>
<tr><td colspan="2">Left
M = 0.42</td><td colspan="2">Right
M = 0.41</td><td colspan="2">Left
M = 0.42</td><td colspan="2">Right
M = 0.42</td><td colspan="2">Left
M = 0.42</td><td colspan="2">Right
M = 0.42</td><td>*</td><td>R < L</td></tr>
<tr><td rowspan="3"></td><td rowspan="3"><i>RM
(3 x 2 x 2)</i></td><td colspan="4">Good News vs, Neutral News</td><td colspan="4">Neutral News vs. Bad News</td><td colspan="4">Good News vs. Bad News</td><td>ns</td><td>--</td></tr>
<tr><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td colspan="2">Left</td><td colspan="2">Right</td><td>ns</td><td>--</td></tr>
<tr><td>P
0.49</td><td>N
0.51</td><td>P
0.48</td><td>N
0.51</td><td>P
0.50</td><td>N
0.50</td><td>P
0.50</td><td>N
0.52</td><td>P
0.50</td><td>N
0.52</td><td>P
0.49</td><td>N
0.50</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2"></td><td rowspan="2"><i>RM
(2 x 2)</i></td><td colspan="6">Single</td><td colspan="6">Double</td><td>***</td><td>Single << Double</td></tr>
<tr><td colspan="3">Left
M = 0.42</td><td colspan="3">Right
M = 0.41</td><td colspan="3">Left
M = 0.50</td><td colspan="3">Right
M = 0.51</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2">MT</td><td rowspan="2"><i>RM
(2 x 2)</i></td><td colspan="4">Neutral News</td><td colspan="4">Good News</td><td colspan="4">Bad News</td><td>ns</td><td>--</td></tr>
<tr><td colspan="2">Left
M = 0.51</td><td colspan="2">Right
M = 0.49</td><td colspan="2">Left
M = 0.52</td><td colspan="2">Right
M = 0.48</td><td colspan="2">Left
M = 0.51</td><td colspan="2">Right
M = 0.48</td><td>**</td><td>R << L</td></tr>
<tr><td rowspan="4"><i>RM
(3 x 2 x 2)

*3-way Interaction (shape pair x Preferred x SoS)</i></td><td rowspan="2">Preferred</td><td colspan="4">Good vs. Neutral</td><td colspan="4">Neutral vs. Bad</td><td colspan="4">Good vs. Bad</td><td>ns</td><td></td></tr>
<tr><td colspan="2">Left
M = 0.54</td><td colspan="2">Right
M = 0.50</td><td colspan="2">Left
M = 0.53</td><td colspan="2">Right
M = 0.52</td><td colspan="2">Left
M = 0.53</td><td colspan="2">Right
M = 0.51</td><td>***</td><td>R << L</td></tr>
<tr><td rowspan="2">Non-Preferred
<i>*Interaction (shape x Sos)</i></td><td colspan="4">Good vs. Neutral</td><td colspan="4">Neutral vs. Bad</td><td colspan="4">Good vs. Bad</td><td>ns</td><td>--</td></tr>
<tr><td colspan="2">Left
M = 0.53</td><td colspan="2">Right
M = 0.53</td><td colspan="2">Left
M = 0.56</td><td colspan="2">Right
M = 0.51</td><td colspan="2">Left
M = 0.54</td><td colspan="2">Right
M = 0.50</td><td>**</td><td>R << L</td></tr>
<tr><td><i>RM
(1 x 3)</i></td><td>Non-Preferred / Left</td><td colspan="4">Good vs. Neutral
M = 0.53</td><td colspan="4">Neutral vs. Bad
M = 0.56</td><td colspan="4">Good vs. Bad
M = 0.54</td><td>ns</td><td>--</td></tr>
<tr><td><i>RM
(1 x 3)</i></td><td>Non-Preferred / Right</td><td colspan="4">Good vs. Neutral
M = 0.52</td><td colspan="4">Neutral vs. Bad
M = 0.51</td><td colspan="4">Good vs. Bad
M = 0.51</td><td>ns</td><td>--</td></tr>
<tr><td rowspan="2"></td><td rowspan="2"><i>RM
(2 x 2)</i></td><td colspan="6">Single</td><td colspan="6">Double</td><td>**</td><td>Single < Double</td></tr>
<tr><td colspan="3">Left
M = 0.52</td><td colspan="3">Right
M = 0.49</td><td colspan="3">Left
M = 0.55</td><td colspan="3">Right
M = 0,51</td><td>***</td><td>R << L</td></tr>
<tr><td>Reach Area</td><td><i>RM
(1 x 3)</i></td><td colspan="4">Neutral News
Area = 289.06</td><td colspan="4">Good News
Area = 290.01</td><td colspan="4">Bad News
Area = 287.37</td><td>ns</td><td>--</td></tr>
<tr><td></td><td><i>RM
(1 x 3)</i></td><td colspan="4">Good News vs. Neutral News
Area = 237.88</td><td colspan="4">Neutral News vs. Bad News
Area = 225.08</td><td colspan="4">Good News vs. Bad News
Area = 234.80</td><td>ns</td><td>--</td></tr>
<tr><td></td><td><i>RM
(1 x 2)</i></td><td colspan="6">Single
Area = 288.81</td><td colspan="6">Double
Area = 232.59</td><td>***</td><td>Single >> Double</td></tr>
<tr><td>Subjective Report</td><td><i>RM
(2 x 2)</i></td><td colspan="4">Neutral News</td><td colspan="4">Good News</td><td colspan="4">Bad News</td><td>**</td><td>Bad << Good/Neutral</td></tr>
<tr><td rowspan="2"><i>*Interaction Shape x Pre-post</i></td><td>POST</td><td colspan="4">M = -3.28</td><td colspan="4">M = 2.60</td><td colspan="4">M = -12.00</td><td>ns</td><td>Good >> Neutral</td></tr>
<tr><td>PRE</td><td colspan="4">M = -15.00</td><td colspan="4">M = 7.80</td><td colspan="4">M = -2.40</td><td>**</td><td></td></tr>
<tr><td></td><td><i>t-test vs. 0%</i></td><td colspan="2">ns</td><td colspan="2">ns</td><td colspan="2">ns</td><td colspan="2">ns</td><td colspan="2">ns</td><td colspan="2">**</td><td>--</td><td>--</td></tr>
</table>

4.0) Discussion

4.1) Results Summary

Here we devised 4 experiments to test how theories of decision making would extend to the value of information regarding rewards. Experiments 1 and 2 were created to examine how humans would behave in a task like the pigeon experiment (McDevitt, Spetch, & Dunn, 1997). In doing so, we sought to test if Uncertainty Reduction Theory (URT) (Kellermann & Reynolds, 1990) and the Temporal Discounting Theory (TDT) (Green, Myerson, & McFadden, 1997) theory would extend to humans such that humans might behave like pigeons and prefer to reduce uncertainty in a timely fashion about future rewards. In our experiments we found this was not the case as subjects were influenced and sensitive to probability contingencies while being impervious to information and the presence of a delay. Specifically, in Experiment 1, subjects chose non-informative shapes with a higher probability of reward more often than the informative, lower probability shapes. This was also reflected in their reaction time and movement times, as subjects reacted and moved faster towards non-informative (high probability) shapes. This effect was not replicated in Experiment 2, presumably because we eliminated imbalanced probabilities and gave all shapes a 50% of offering a reward. In both Experiments 1 and 2, there was a pronounced side of space bias, where subjects moved faster towards shapes on the right side of space. Additionally, subjects reacted/moved faster in single target trials compared to paired target trials in both Experiments 1 and 2. For reach area, Experiments 1 and 2 showed a much larger reach area for single target trials compared to paired target trials, suggesting that paired trials involved more indecision. Lastly, for subjective reports in Experiment 1, subjects felt that they were being rewarded for informative shapes roughly 5% more than they were being rewarded for non-informative shapes. Consequently, for non-informative shapes, they reported approximately 20% less reward than they were receiving. Even though they preferred the non-informative targets which offered a 65% chance at receiving a reward, they felt they were being paid off only 45% of the time.

Experiments 3 and 4 were designed to test if the Signal of Good News (SiGN) (Mcdevitt, Dunn, Spetch, & Ludvig, 2016) theory extended to humans and whether loss aversion (a component of Prospect Theory) (Tversky & Kahneman, 1992) extended to information about a reward, rather than just the reward itself. In Experiments 1 and 2, we found no evidence that our human participants valued information. However, in Experiments 3 and 4 we wanted to know if part of our failure to find this preference was due to the valance of information (good or bad news). Specifically, if people like good news and avoid bad news, these may have cancelled each other out in Experiments 1 and 2. If this was true, Experiments 3 and 4 also allowed us to test if there was an asymmetry in this bias – for example people might prefer receiving good news more than they avoid bad news (or vice versa). Structurally, Experiment 4 was identical to Experiment 3, except for numerical feedback being present at the end of each trial. For choice preferences, subjects generally valued good news when paired with neutral or bad news, with more pronounced effects in Experiment 3. In Experiment 3, subjects overwhelmingly opted for good news when paired with neutral news or bad news and for neutral news when paired with bad news. Regarding reaction and movement time in Experiments 3 and 4, we see a trend for right sided bias like Experiments 1 and 2. Furthermore, in Experiment 3, subjects reacted faster towards good news compared to neutral or bad news shapes. In Experiment 4, subjects reacted faster toward preferred shapes over non-preferred shapes in the paired target trials. In addition, subjects reacted and moved faster towards single target trials compared to paired trials. Reach area perhaps revealed the most telling story for Experiments 3 and 4. In Experiment 3, reach trajectories revealed that the good vs. bad news condition presented the easiest motor decision (denoted by the largest reach area), followed by good vs. neutral, leaving neutral vs. bad to be the hardest decision. The pattern was similar, though not significant in Experiment 4. Lastly, subjective reports revealed that participants detested bad news in Experiments 3 and 4. In both post-experiment questionnaires, they reported that bad news paid off at a much lower rate than good or neutral news. Bad news was the only shape that was largely distant from the actual pay-off of 50%.

4.2) No effect of information or delay in experiment 1 and experiment 2

The most pressing questions that needs to be answered is why do humans not value immediate information in the same way pigeons do? What is it about human cognition that separates us from pigeons when it comes to decision-making under uncertainty? Secondly, why does temporal discounting change the behavior of the pigeons, but not humans? Are these discrepancies due to the experimental framework of the task? Or are there innate differences between how humans perceived temporal discounting and how pigeons perceive it? In the next series of sections I address different issues that I feel may have contributed to the differences observed between our results with humans and the previous result in pigeons.

4.2.1) Humans are most sensitive to probabilities, even if they are not aware

In Experiment 1, we presented shapes that offered more reward against shapes that offered more information. This was a human adaptation of McDevitt, Spetch, & Dunn (1997) experiment with pigeons. In this study, we sought to know if humans value immediate information over no information, or potential reward in a reaching decision-making task. Given the past pigeon work, we predicted humans would seek to reduce uncertainty about their decision by selecting informative shapes. In violation of this prediction, in Experiment 1 subjects clearly preferred non-informative, high probability shapes. Whenever non-informative shapes were paired with informative shapes, subjects selected non-informative shapes close to 70% of the time as seen in figure 3.1. The only two shape pairs close to 50% were when both non-informative or both informative shapes appeared together. Looking at choice preferences in Experiment 1, subjects largely disregarded seeking information. Rather, they chose to remain uncertain to maximize expected value by opting for the high probability, non-informative shapes. According to the URT (Kellermann & Reynolds, 1990), humans should have valued immediate information over delayed, or no information, as the pigeons did.

Because of our higher order function, humans may assimilate differently to uncertain situations compared to pigeons. According to Lipshitz & Strauss (1997), uncertainty in humans can be distinguished among three types - inadequate understanding, incomplete information, and undifferentiated alternatives. Incomplete information is the type of uncertainty presented in our study. To cope with incomplete information, humans can employ certain tactics which may contain collecting additional information or deferring decisions until new information becomes available. This becomes particularly relevant when humans were making decisions from many past experiences rather than a classic, descriptive-based economic decision task where respondents make a single choice and all outcomes and probabilities are stated (Hertwig, Barron, Weber, & Erev, 2004).

Decisions based on past experiences involve learning the probabilities of your options implicitly (Hertwig & Erev, 2009). Through trial-by-trial feedback, humans can overcome incomplete information by learning the about the probability structure of their task, and predicting future events based on past events (Allaire & Firsirotu, 1989; Bernstein & Silbert, 1984; Luce & Suppes, 1965). This is vastly different from a description-based task whereby responders are given a novel monetary gambling scenario with explicitly stated probabilities and outcomes. In these types of tasks, people commit heuristic errors by overvaluing rare events, a fallacy consistent with the prospect theory (Kahneman & Tversky, 1979). This is known as the description-experience gap, and there are several reasons why people commit this miscalculation (Hertwig & Erev, 2009; Hau, Pleskac, Kiefer, & Hertwig, 2009). The main reason for the description-experience gap is the reliance on small sampling. Description-based tasks do not involve enough samples for an agent to learn or experience a rare event. Thus, they are more likely to undersample than to oversample a rare event (Hertwig & Erev, 2009; Hau, Pleskac, Kiefer, & Hertwig, 2009). This may cause responders to be more risk-averse, fearing the uncertainty of potential negative outcomes (since they overweight lower probabilities of losing). However, our task exists in the experience-based domain, where participants learned about the probability contingencies through trial-by-trial feedback and were able to predict how often each shape paid off points. Judging by the choice preferences in Experiments 1 and 2, subjects shaped their behavior based on the reward feedback they received after every trial and eventually learned that non-informative shapes offered more reward than informative shapes (in Experiment 1). Receiving full feedback after every trial gave users an implicit insight into probabilities, and they were sensitive to it. In Experiment 2, when all shapes were equiprobable, users likely learned that all shapes paid off equally, and this was reflected in their choice preferences, which were all statistically at chance.

Experiment 2 reinforced that choice behavior was primarily being driven by probability contingencies. As mentioned earlier, humans, not unlike monkeys, can learn probability contingencies and one mechanism thought to support this learning are the dopamine dependent reward prediction errors in the striatal pathway of the brain shown by Pessiglione and colleagues (2006). In their study, subjects were placed in three groups. One group was placebo-treated, one group was administered L-DOPA (an amino acid that is a precursor for dopamine), and one group was given haloperidol (an antagonist of dopamine receptors). Subjects performed an instrumental learning task involving monetary gains and losses, which required selecting stimuli displayed on a computer screen, to maximize payoffs. Each stimulus was given a certain probability of gain or loss (0.8 gain, 0.2 loss). These stimuli were placed in pairs and subjects had to select between them to maximize expected gain. Subjects in the L-DOPA group won more money than subjects in the haloperidol group, suggesting that enhancing dopaminergic activity improved choice performance towards monetary gains (Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006). Dopamine-dependent activity in the striatal brain facilitated choice behavior by using reward prediction error to improve future decisions. Relating this kind of learning to our experiments, in Experiment 1, subjects likely learned which shapes offered more points through reward prediction error, and that is what drove choice behavior. In Experiment 2, subjects came to implicitly understand that all shapes were equiprobable, which convoluted and eradicated any preference or pattern. To summarize, choice preferences revealed that subjects were sensitive to the probabilities of each shape in Experiments 1 and 2.

The preference for higher probability shapes was also seen in other dependent measures in Experiment 1. In single shape trials, subjects reacted faster towards high probability, non-informative shapes compared to informative shapes. In the early steps of perceptual processing, preferred targets may be processed faster than non-preferred targets (Chapman, Gallivan, Wong, Wispinski, & Enns, 2015). Furthermore, in the paired trials in Experiment 1, subjects reacted and moved faster to preferred shapes (in general, higher probability) compared to non-preferred shapes. This reinforces the notion subjects processed and responded faster to shapes they preferred hitting.

To summarize, instead of being attuned to information, participants were largely influenced by the probability contingencies offered in Experiments 1 and 2, something they had to learn throughout the task. In the next section we explore what behavioural strategies could lead to contingency learning, or, probability matching.

4.2.2) Behavioral strategies for probability learning

Since choice behavior was dominated by probability sensitivities in Experiments 1 and 2, it is useful to consider what strategies people could have employed that led to this behavior. At the highest level, our experiment falls into a broad range of studies examining foraging-like behavior where participants must conduct an "explore-exploit" trade-off (Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006). This trade-off requires subjects to select between multiple reward options where the value of each option is initially unknown. To learn which options offer the most reward, the subject will trade off "known" options for less familiar options to gain more information about future decisions. In Experiment 1 with asymmetrical probabilities, subjects traded off known options near the start of the task only to learn that non-informative shapes offered more reward later, regardless of the delay. For example, in the first experimental block of trials, subjects only selected high-probability shapes 36% of the time. By the last block of the experiment, subjects were selecting high probability shapes 84% of the time. This suggests that subjects were exploring all options early in the task, only to exploit higher probability shapes near the end. In Experiment 2, the "known" options were truly random in terms of reward pay off, which left subjects guessing at almost every shape pair (~50% in the first experimental block, and ~50% in the last experimental block for all shapes).

A specific example of a behavioral strategy that employs a simple heuristic to implement the explore-exploit trade-off is the win-stay, lose-shift theory (Barraclough, Conroy, & Lee, 2004). In an environment where the agent must complete a set of defined actions for an unknown payoff or penalty, a mixed strategy (e.g. sometimes exploring and sometimes exploiting) may be optimal. This is especially true when the task involves selecting between two choices (Paulus, et al., 2001). Moreover, a simple tactic for how to engage this mixed strategy is to continue exploiting (e.g. sticking with) options that reward (win-stay) and exploring away from options (e.g. switching) that do not reward (lose-shift). Studies have shown that this strategy is feasible even when the correct choices are random. Despite random reinforcement, subjects do not respond randomly, but use an algorithmic approach to explore all options (Paulus, et al., 2001). In Experiment 1, this strategy proved somewhat fruitful, as subjects who won with a certain shape, stayed with that very shape on the next trial (containing that shape) 67% of the time. While shapes they lost upon hitting, shifted to another shape on the next trial shifted away 45% of the time. In E2, however, subjects would have been in a constant flux of win-stay, lose-shift, setting an equilibrium across all shapes, regardless of their information/delay. Subjects only "win and stayed" 60% of the time in E2, and "lost and shifted" 50% of the time. These values show that the subjects may have been using other strategies in conjunction with the win-stay, lose-shift tactic.

4.2.3) Humans can learn to wait

As with the URT, the TDT failed to register with the human subjects in our experiment. That is, while pigeons will reverse their preference for good news as soon as that news is delayed (McDevitt, Spetch, & Dunn, 1997) in Experiments 1 and 2 our participants did not indicate any preference for immediate information. One reason this likely occurred was because our delays were significantly shorter (2 s and 4 s) than those used in the pigeon study (30 s). However, we believe that this lack of an effect may also be due to animals, like pigeons, discounting delayed rewards much more steeply than humans.

Typically, humans can account for future consequences when making temporal decisions, whereas animals typically only wait a few seconds for delayed benefits (Rosati, Stevens, Hare, & Hauser, 2007). Future-oriented decisions are much more evolved in humans and closely related species (chimpanzees) compared to birds or rodents. This phylogenetic gap between humans and birds/rodents suggests considerable discrepancies for discounting when it comes to rewards. Evolutionary psychologists suggest that humans and chimpanzees adapted differently to foraging strategies, specifically saving or holding onto food in case of a potential drought in the future. For example, chimpanzees inhabited environments with unpredictable food availability, which forced them to postpone eating all their food right away (Rosati, Stevens, Hare, & Hauser, 2007). Chimpanzees commonly tolerated higher additional costs to acquire food, such as increased work effort, longer travel distances, which may have given way to temporal costs. Birds or rodents appear to have a radically reduced timescale for their foraging costs, thus making them more impulsive. This becomes especially true when examining the type of diet these animals need (Rosati, Stevens, Hare, & Hauser, 2007).

Ecological differences between two closely related primates, marmosets and tamarins show different levels of patience and self-control. The authors state that marmosets specialize on plants, where they must exert patience and modified discounting when waiting for the gum or sap from a leaf to ooze out, allowing them to evolve their ability to value future rewards. Therefore, the self-control needed to feed on sap may have selected for a more general ability to delay gratification (Stevens, Hallinan, & Hauser, 2005). Tamarins on the other hand, feed on insects, and requires greater impulsivity to capture a difficult moving target (Snowdon & Soini, 1988). If two closely related primates share significantly different levels of patience and self-control, imagine the extreme differences that could have arisen given the evolutionary arc that humans underwent. Here, we share some perspectives on why humans were not affected by temporal discounting in this task compared to the pigeons. The evolutionary arc for humans supports the idea that people can account for future consequences when making temporal decisions, unlike some animals. Pigeons quickly changed their preference for information when it was temporally discounted, ironically making their behavior more optimal. However, humans were not deterred by the presence of a temporal delay in Experiment 1, likely because they were aware that the pay-offs were more of a priority than waiting.

This notion of patience goes one step further with humans. Although we share similar patience levels with apes, we have evolved a greater capacity for patience beyond primary rewards. Reward types, such as money have shaped human patience and discounting (Rosati, Stevens, Hare, & Hauser, 2007). Money is unlike any primary reward, since it is storable, convertible and can take on extremely large values. Furthermore, humans will forgo temporal impulsivity to ensure they maximize their expected rate of gain when it pertains to money (Kacelnik, 2003). Also, limited exposure to money can alter goals and behavior in humans, with cognitive and basic reward circuits overlapping (Vohs, Mead, & Good, 2006). Humans underwent evolutionary and civilizing pressures to systematically acquire the trait known as patience or self-control. Secondary rewards such as money have changed the way humans temporally discount rewards, allowing them to exert more patience for a longer, but greater payoff. In Experiment 1, humans likely weighed the cost of an additional 2 s against potential reward and exercised their unique practice of patience to maximized expected gains.

This of course highlights a second difference - humans in our task were dealing with points, which is a secondary reward, like money. By comparison, the pigeons were starved and were working for food an immediate and essential primary reinforcer (Mcdevitt, Dunn, Spetch, & Ludvig, 2016). The difference between primary and secondary reinforcers is addressed in the next section.

4.2.4) Primary vs. Secondary reward

There are conflicting views on the representation of primary and secondary rewards in the brain (Delgado, 2007; Knutson, Adams, Fong, & Hommer, 2001; O'Doherty, Rolls, Francis, Bowtell, & McGlone, 2000; Delgado, Labouliere, & Phelps, 2006). While primary rewards consist of responses to things like food, sex, and drugs, secondary rewards may consist of money, points or in some cases, information about a primary reward. Some suggest that differing areas of the brain process primary and secondary rewards (Delgado, 2007), while others proclaim there is an overlap in the ventral striatum (which includes the NAc) for primary or secondary rewards (Knutson, Adams, Fong, & Hommer, 2001; O'Doherty, Rolls, Francis, Bowtell, & McGlone, 2000). This is an important topic to investigate because our study looked to recreate the McDevitt, Spetch, & Dunn (1997) pigeon experiment, except there was one major difference. Pigeons were performing for primary rewards, while our task had humans performing for secondary rewards (points), This may be a possible reason why pigeons behaved differently than humans.

Some converging evidence suggests that primary and secondary rewards are processed in similar brain areas. An interesting brain region that seemingly deals with primary and secondary reinforcers across humans and animals is the amygdala (Martino, Camerer, & Adolphs, 2010; Orsini, Trotta, Bizon, & Setlow, 2015). In humans, the amygdala is thought to be related to assessing loss aversion in a monetary task. Specifically, when the amygdala is lesioned, participants were still able to respond accordingly in a gambling task but showed a dramatic increase in risk-taking gambles compared to control participants (Martino, Camerer, & Adolphs, 2010). That is, the amygdala helps assess risk when dealing with secondary rewards. Additionally, the amygdala is also an area that is thought to processes primary punishment. Orsini, Trotta, Bizon, & Setlow (2015) investigated the role of the amygdala on rats who were trained in a risky decision-making task where they chose between two levers, one that delivered a small safe reward and the other which delivered a large reward but was accompanied by varying shock intensities. Rats that had their basolateral amygdala removed showed little sensitivity to punishment, opting for the risky reward more often than the sham control rats. These studies help confirm that specific brain areas, such as the amygdala respond to primary and secondary reinforcers in both animals and humans.

Other studies suggest that primary and secondary rewards are processed by different brain areas. Neurologically, responses to secondary rewards are observed in the anterior part of the orbitofrontal cortex, which suggests these rewards are represented in more recently evolved, higher developed brain areas. In contrast, primary rewards are represented in the anterior insula, and the amygdala (Sescousse, Caldu, Segura, & Dreher, 2013). This is further supported by Grimm & See (2000), who examined the effects of self-administered cocaine in rats whom, in addition, received a secondary reward (information) during their task. They specifically inactivated the basolateral amygdala or Nucleus Accumbens (NA) using tetrodotoxin (TTX). After doing so, they found that only the basolateral amygdala attenuated secondary rewards (tone + light) for the rats, while the NA resulted in a significant blockade of the primary reward (cocaine alone), but not secondary rewards. They concluded that cocaine-conditioned reward is dissociated from primary cocaine reward in the brain (Grimm & See, 2000). These findings reinforce the fact that secondary rewards are handled different than primary rewards in the brain.

A dissociation in the neural responses to primary and secondary rewards appears particularly pronounced in the loss domain. In a study conducted by Delgado, Jou & Phelps (2011), participants were subjected to two different aversive conditioning tasks. One was for negative primary punishment in the form of a mild shock, and secondary punishment in the form of monetary loss (- $4.00). During this task, skin conductance and exploratory fMRI analysis revealed higher skin conductance responses for primary punishments, and a larger BOLD response in some fundamental brain areas such as the cingulate gyrus, anterior and posterior insula and the somatosensory cortex. Specifically, the amygdala was found to be more active in the primary task, suggesting that it is largely dedicated to the presence of primary rewards/punishments. Irrespective of the type of punishment, the striatum was found to be active during the acquisition of conditioned responses, suggesting it plays some role in stimulus learning (Delgado, Jou, & Phelps, 2011). Overall, underlying neural mechanisms have shown that primary and secondary losses can be represented differently in the human brain.

To summarize, we've shown that there are conflicting ideas on the processing of primary and secondary rewards in the human brain. While some areas such as the amygdala have shown a linkage between both types of rewards, other areas such as the NAc, cingulate gyrus, and the somatosensory cortex have shown extensive processing for primary rewards over secondary ones. In relation to our study, we created a reward horizon centered around secondary rewards (points). When comparing human behavior to the pigeon task, it is not surprising that humans were not as invested in seeking information, since the reward was not of primary nature. Thus, this serves as a limitation for us, seeing as pigeons were working for primary rewards and our humans participants were not.

4.2.5) Good and bad news cancel

Finally, a last possible reason why we failed to find an effect of information in Experiments 1 and 2 is ultimately what motivated Experiments 3 and 4 – that the effects of good and bad news cancel. In Experiments 1 and 2, informative shapes were always informative of both good and bad outcomes. So – a person who wanted to receive good news, but was also averse to bad news, might have had these two inclinations balance out. This would stand in direct opposition to URT which argues that any news, good or bad, will reduce uncertainty is therefore valuable and will be treated the same. However, there is precedent in the literature to think that people process good and bad outcomes differently, and here we think this might extend to the information domain (Chapman, et al., 2015; Kahneman, 2011; Tom, Fox, Trepel, & Poldrack, 2007).

Why do pigeons prefer informative targets and not humans? It appears humans and pigeons behaved differently when confronted with a target that contained potentially bad information about a reward outcome. Pigeons show a dominant preference for good news and are largely unaffected by bad news, whereas humans have been shown to be more sensitive to potential losses (Tom, Fox, Trepel, & Poldrack, 2007). This may be a key insight into why humans avoided informative shapes. In the pigeon paradigms, several bits of evidence have shown that good news is valuable and provides reinforcement for responding, whereas bad news, while informative, does not have a negative or positive effect (Mcdevitt, Dunn, Spetch, & Ludvig, 2016). Mcdevitt & Spetch (2016) speculate that good news functions differently than bad news because food requires organisms to engage in preparatory behaviors, and signals for the absence of food does not require such preparedness. For humans, seeing bad information and missing out on potential points does not require such preparedness, yet they clearly avoid such shapes. Part of this reasoning may be due to loss aversion, where people are more sensitive to losses than equivalent gains (Tom, Fox, Trepel, & Poldrack, 2007; Kahneman & Tversky, 1979). This will be discussed further in section 4.3.2. Thus, when pairing good and bad news into one shape, humans may have avoided these shapes in E1 and E2 because of their asymmetrical sensitivity to losses over potential gains. In contrast to the pigeons, who showed no real loss-averse behavior to bad information, thus were willing to select informative shapes more often.

To reiterate, having valanced information coalescing into one shape disrupted the signal for good news in humans because bad news was also present. Since humans may be more attuned to potential losses than gains (likely more so than pigeons), they steered away from targets that offered potentially bad news. This became a point of contention, and we sought to change that in Experiments 3 and 4 by isolating good and bad news into their own shapes. By doing so, we were able to assess the sensitivity preference domain for good, bad and neutral news, something we couldn’t execute in Experiments 1 and 2.

4.3) Humans seek good news and avoid bad news

The fundamental questions behind Experiments 3 and 4 were derived from the SiGN and loss aversion theories, both of which argue that the valence of a reward (or information) effects how it influences behaviour. In Experiments 3 and 4, we moved to 3 shapes (good, bad, neutral information) that all offered a 50% chance of receiving points. Of those 3, good and bad news shapes only revealed information 25% of the time, while the remaining 75% offered no-information (blue color change). Transitioning from Experiments 1 and 2 we also removed the delay factor, since it did not have any effect on behaviour. For Experiment 3, we removed numerical feedback at the end of each trial and provided a running total update at the end of each block. This enhanced the value of information because subjects had no other way of knowing they were rewarded during the blocks. However, it also introduced a potential confound as the information might have been treated as the actual reward. Therefore, as a control measure, we reintroduced numerical feedback in Experiment 4 to see if choice preferences would remain constant. This means that any effects observed due to information in E4 were caused by only one second of advance knowledge about the outcome of a trial on only 25% of trials for a given shape. Overall, in both Experiments 3 and 4, subjects preferred seeking good over bad or neutral information. Subsequently, they avoided bad news wherever they could. The next section will interpret and elucidate human's preference for good information.

4.3.1) The preference for good news

The preference for good news over all other options was consistent and compelling in choice preferences and reach trajectories. In both Experiment 3 (figure 3.5A) and Experiment 4 (figure 3.5B) any time the good news shape was an option, it was selected significantly more than whatever it was paired with. Thus, even though all shapes were equiprobable, and as demonstrated in Experiments 1 and 2, participants are generally sensitive to probabilities, in Experiments 3 and 4 there was a strong preference for shapes providing good news. This aligns with the predictions made by the SiGN theory - in a 50/50 gamble, the unexpected presence of good news for an option may reinforce selection of that option.

The proposed mechanism for this reinforcement is tied to the concept of prediction error – an unexpected consequence. In this case, the appearance of a good news signal may trigger a prediction error in the striatal pathway, releasing dopamine upon the presence of the good news signal (Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006). It is this large positive reward prediction error (this shape is unexpectedly good) that was reinforcing to the subject, much the same as the pigeons. As an example, imagine a worker receives a cheque of $1000 dollars every two weeks from his employer. He acknowledges and understands he will receive the same money on the same day every 2 weeks. Therefore, he will not be surprised when he receives his cheque because he anticipates it. Thus, little to no reward prediction error will be stimulated in his ventral striatal pathways. Now, imagine one day, he purchases a lottery ticket to win a $1000-dollar prize. Upon purchasing this ticket, he understands that his odds of winning are very low, so he expects to lose on this lottery purchase. To his surprise, he later finds out he has won the $1000. Considering his reference point before winning, a large reward prediction error will be signaled in the brain, and this release of dopamine will carry large intrinsic value, such that the lottery $1000 will seem more rewarding than the pay cheque $1000. Because he expected to lose the lottery, but won, this shift in reference point will be relayed in the brain, as dopamine will release upon learning the news that he won the lottery. In a way, the information that he received about the lottery was rewarding in and of itself. That this preference for good news extends to Experiment 4 is particularly surprising because in that experiment subjects received numerical feedback 1 s later, and this should have realistically reduced the preference solely for a good signal because numerical feedback acted as the primary reinforcer. Keep in mind that all shapes rewarded points 50% of the time. The numerical feedback should be the reinforcing factor that drives behavior, and yet, there was still a strong preference for good news instead. It may be the combination of a good news signal and the subsequent reward that drives behavior in this decision-making task, as all shapes reward equally. By examining choice preferences in Experiments 3 and 4, there is evidence that humans strive to seek good information about a reward, especially when all shapes are equiprobable. Here, the signal for good news extends past primary rewards to information.

One way of understanding the reinforcing nature of unexpected positive information is to consider it as a surprise signal. Surprise and novelty are two factors that may have contributed to the preference for good news (Gottlieb, 2012; Gottlieb, Lopes, & Oudeyer, 2016). Surprise, in the visual domain, is defined as the divergence between prior and posterior beliefs about visual stimuli. Specifically, it is the extent to which a visual input changes the observer's belief. It is closely related to SiGN in that an unexpected change in belief about a stimulus can activate dopaminergic release in the NAc, reinforcing the behavior (Gottlieb, Lopes, & Oudeyer, 2016). This is analogous to a magician's ability to manipulate our expectations based on misleading visual information. Through manipulating incoming sensory information, a magician can misdirect, then surprise. However, predictive coding theories hypothesize that the brain filters out redundant information, allowing for resources to be allocated to significant items (Gottlieb, Lopes, & Oudeyer, 2016; Friston, et al., 2013). This is a critical systematic removal, because it allows us to allocate attention to the right areas, assisting in our odds of survival. In Experiments 3 and 4, the signal for good news only appeared 25% of the time on one shape, making it a "significant item", while the remaining 75% offered ambiguous information. Since receiving good news garnered intrinsic reward, it is likely that participants honed in on the surprise of the signal considering it was surrounded by redundant information.

In conjunction with surprise, novelty is defined by the total amount of exposure that observers had to a given observation (Barto, Mirolli, & Baldassarre, 2013; Gottlieb, Lopes, & Oudeyer, 2016). Neurologically, novel stimuli have been shown to activate the same midbrain dopaminergic structures as reward-based stimuli (Horvitz, 2000; Laurent, 2008). Gottlieb, Lopes,

& Oudeyer (2016) examined the effects of novelty and reward on the brain. They trained monkeys on a task where they received visual cues that were either novel or familiar, and brought potentially good or bad information with regards to a reward at the end of a trial. They recorded from visual areas such as the lateral intraparietal area (LIP) and the frontal eye field (FEF), which selectively encode locations of attention-worthy stimuli. For familiar and positive cues, neurons in the LIP showed slight excitation, and familiar and negative cues signalled slight inhibition. However, novel cues showed enhanced responses for both positive and negative news. But for positive novel cues, monkeys showed increased anticipatory licking, indicating that they were expected good news. This licking was extinguished if the cue turned out to be bad news. These results show that novelty of a stimulus is given preferential treatment in the visuo-attention systems of the brain (Gottlieb, Lopes, & Oudeyer, 2016). While enhanced activity was seen for both positive and negative novel cues, monkeys showed a behavioral preference for only good news by increasing anticipatory licking. To reiterate, novel stimuli are reflective of enhanced activation in the brain, regardless of valence. However, monkeys revealed a behavioural preference for good novel information by increasing their anticipatory licks in comparison to novel bad stimuli. In Experiments 3 and 4, the novelty of a stimulus resided in the pure good or bad signals given off by the shapes. Over the course of 528 trials, a good or bad news signal appeared 132 times, making it novel compared to ambiguous news. Therefore, it is conceivable to think that humans showed additional attention to novel signals, especially good news.

In addition to the choice preference for good news in Experiments 3 and 4 there is some evidence from other dependent measures such as RT, MT and reach area to reinforce our interpretation of a preference for good-news shapes. With regards to RT and MT, in Experiment

3 subjects moved faster towards shapes they prefer, in this case, the good news shapes. And, in Experiment 4, for MT, it appears as if the valence of a target was affecting movement speed. Several lines of evidence have shown that, in the earliest perception responses, preferred targets are processed faster than non-preferred targets (Kahneman, 2011; Chapman, Gallivan, Wong, Wispinski, & Enns, 2015). For reach trajectories, early preferential processing came in the form of straighter trajectories towards good news targets as seen in figure 3.10, a pattern that was significant in Experiment 3 and in the same direction in Experiment 4. However, an important caveat when interpreting these other measures is that they occur almost exclusively in Experiment 3 where, in the absence of trial by trial feedback, it is possible that the news signal itself came to represent the primary reward. Therefore, we are tentative in our statement of these results and feel the strongest evidence for a good news preference still comes from the choice behaviour.

4.3.2) The avoidance of bad news

Our intuition for creating Experiments 3 and 4 was contingent on the idea that subjects might both prefer good news and avoid bad news, thereby accounting for the null results in Experiment 2. Here, we discuss evidence from our experiments that loss aversion extends into the information domain. This was seen most prominently in the subjective reports and choice preferences (%) in Experiments 3 and 4. In Experiment 3, for the critical choice between a neutral and bad news shape, there was a significant preference (%) to avoid bad news and select the neutral shape. This preference extends to Experiment 4 (%) where our results did not pass a stringent corrected p-value of 0.017 (0.05/3) but were conventionally significant at $p = 0.02$. In these trials, subjects gladly chose to remain ambiguous over “losing” a 50/50 gamble. That is, subjects steered clear of the bad news shape because they were at risk of receiving a bad signal, which indicates a loss – put simply, they would rather not know then know that something bad was going to happen. This notion is reminiscent of the Ganguly & Tasoff (2016) study discussed in the introduction, which found that humans were three times more likely to avoid testing for HSV-2 (the more serious herpes simplex virus) compared to HSV-1, a less detrimental type of herpes, suggesting that more aversive outcomes lead to more information avoidance.

Beyond choice percentages (%), subjective reports gave us the biggest indicator of loss aversion. When asked about subjective payoffs for each shape in Experiments 3 and 4, subjects overwhelmingly reported bad news shapes as offering the least amount of reward, even though all shapes were equiprobable. The subjective reports for Experiments 3 and 4 helped confirm some predictions we made with regards to loss aversion. In Experiment 3, subjects filled out a subjective report twice — once after the training trials were complete (numerical feedback was included during training), and once after the end of the experiment. We found that subjects were somewhat able to detect probability contingencies just from the training block. Subjective reports for all shapes were within 15% of actual reward pay offs (50%). The post-experiment questionnaire revealed that subjects were extremely averse to bad news. They felt bad news was rewarding them 25% of the time, while reporting that good news was rewarding them 60.5% of the time, and 54.3% for neutral news. To summarize, subjects felt as though bad news was paying off points significantly less than 50%, while good and neutral news was reported to be slightly overvalued. Loss aversion states that losses are weighted significantly more than equal gains (Sabrina, Fox, Trepel, & Poldrack, 2007). Here in Experiment 3, subjects greatly exaggerated the value of the bad news shapes compared to good or neutral news, displaying that bad news was significantly worse than the rest. Again, this effect is likely enhanced in Experiment 3 because subjects misconstrued the value of the information with the reward itself.

However, examining the subjective reports in Experiment 4, we do see a similar trend as seen in figure 3.11B. Again, in the post-experiment report, subjects intuitively rated bad news as paying off 38% of the time. This is a stark change from the pre-report, where they rated the bad news shape close to 50%. This is somewhat fascinating because subjects showed significant probability sensitivity correction for good and neutral news from the pre to post reports. Only the bad news shape was intolerant to probability sensitivity, likely because of loss aversion.

Subjects eventually learned of the probability contingencies for each shape, and their subjective reports from pre to post reflected this finding with values nearing 50%. The only exception to this trend was bad news, where subjects veered further away from the actual value, and rated bad news as paying off significantly lower than 50% as seen in figure 3.11B. As well, all indications of loss aversion were seen strongly in the post-questionnaires compared to the pre-questionnaires. The avoidance and undervaluing of bad news shapes helps reinforce the behavioral aspect of loss aversion in humans. It seems that participants ignored the bad news shape simply because it offered a negative signal about a non-reward trial.

Selective attention to valanced information is not a new or novel finding in humans. Empirical research in psychology has shown that people have the capacity to attend to certain information and ignore others. This is known as the selective hypothesis theory and has been well explored in the world of economics (Caplin & Leahy, 2001). Karlsson, Loewenstein, & Seppi (2009) further examined this linking information acquisition decisions to the hedonic utility of information. In their task, they had individuals receive preliminary, but incomplete information and then decided whether to acquire and attend to the definitive information. They wanted to see how individuals regulated the impact of potentially good or bad news by how intently they attended to the news. They showed that if participants anticipated a negative outcome, they would shield themselves from the information, effectively avoiding it. This is known as the ostrich effect (Karlsson, Loewenstein, & Seppi, 2009). Given bad news, people may optimally choose to avoid collecting additional information: They “put their heads in the sand”. In contrast, given favorable news, individuals seek out definitive information. Given the context of our experiments, it is entirely possible that participants learned that one shape seemed to offer bad news some of the time. Over the course of the experiment, they may have employed the ostrich effect, ignoring bad news shapes, and opting for ambiguous or good news. Given that, the presence of bad news was disproportionately reported as less rewarding than the rest of the shapes in the subjective reports of Experiments 3 and 4. A combination of loss aversion and the ostrich effect may have been seen in the subjective reports.

To summarize, loss aversion was most explicitly seen in the subjective reports, where subjects had to time to reflect on how often each shape paid off points. This is seen most obviously in the post-experiment subjective reports of Experiments 3 and 4, where subjects had time to logically calculate and reminisce upon the gains and losses they experienced. This is consistent with and idea forwarded by Kahneman that, given enough time to consciously think about decision-making, losses will loom larger than gains. We return to this point in section 4.5.

4.4) Other biases revealed in this experiment

While not the main objective, we also report two other biases that were evident in these experiments – a preference for right hand objects and the effects of decision difficulty on behavior.

A strong, right side of space bias appeared for both RT and MT across many statistical tests. Subjects reacted and moved faster toward single targets on the right side vs. left. They also move/reacted faster to right shapes in the paired trials. Since all subjects were right handed in this task, it is not surprising to think they reflected a bias to the right side of space. From a biomechanical standpoint, subjects accrued less mechanical cost moving to the right side of space as opposed to the left (Gallivan & Chapman, 2014). Moving to the left side of space would require subjects to move their elbow and their shoulders, whereas the right side would require mainly an elbow extension. Secondly, there is some speculation that reaching actions are formulated more efficiently toward right side targets due to hemispheric specialization of target processing (Serrien, Ivry, & Swinnen, 2006). Thus, reaching actions to the right side of space from right handed participants reflects faster RTs and MTs.

When examining paired target trials vs. single target trials in all 4 experiments, subjects responded and moved faster to single target trials, by quite a fair margin. The single/paired target x side of space RM-ANOVAS for RT and MT in almost all experiments showed a main effect for single/double targets. Subjects were faster reacting when there was one shape on the screen vs. two. This is no surprise, as deciding between two targets requires longer processing than selecting a single target on screen (Gallivan & Chapman, 2014). This was reflected in the RTs and MTs seen through Experiments 1 to 4.

4.5) A matter of time – how decision biases evolve from "go for good" to "avoid bad"

Decision biases are not static but change according to different time scales (Chapman et al, 2015; Welsh, Neyedli, & Tremblay, 2013; Neyedli & Welsh, 2012; Kahneman, 2011). In our experiments, we discovered that decision biases did exist throughout our tasks. Namely, in Experiment 1, subjects committed to selecting higher probability shapes over informative shapes by a fair margin. In Experiments 3 and 4, participants preferred selecting good news and largely avoided bad news. However, a closer look at the exact dependant measures that seem to carry these biases reveals interesting differences, which here we interpret as indicating that these different biases play out on different time scales. In early perceptual decision domains, gains are preferentially processed over losses (Chapman et al, 2015; Welsh, Neyedli, & Tremblay, 2013; Neyedli & Welsh, 2012). Humans will react faster towards stimuli that offer greater reward in the early, perceptual stages of visuomotor decision-making, while largely disregarding any other options.

The idea that different biasing factors might affect decision making at different timelines is consistent with Daniel Kahneman's two systems of thinking, "Fast" and "Slow" (2011). According to Kahneman (2011) "System 1" is thinking fast, where automatic, implicit, and almost involuntary processes take over when quickly deciding between various options. When operating within the confines of system 1, attentional processes guide fast visuomotor decisions toward potentially gain stimuli. In our experiment, measures such as RTs and MTs, which are largely representative of early perceptual decision-making, showed that subjects reacted and moved faster towards higher probability shapes in Experiment 1 and good news shapes in Experiments 3 and 4. In contrast, potential loss stimuli appear to require additional processing. This taps into Kahneman's (2011) "System 2" of thinking slow, where top-down processes are present, and humans can think, ponder and weigh decision outcomes. In using system 2, humans activate potential emotional regions of the brain, which can heavily influence decisions, especially if losses are potentially looming. This pattern is consistent with our data: across our four experiments, there are clear signs of early preferential processing for positive information and reward. Subsequently, there are indicators that, given sufficient time to ponder and reflect on the task, loss aversion appears.

4.5.1) Early perceptual biases: Go for good!

Early perceptual decision metrics such as RTs, MTs and reach trajectories show a preferential processing bias towards rewarding/informative targets (Chapman et al, 2015; Gallivan & Chapman, 2014; Welsh, Neyedli, & Tremblay, 2013; Neyedli & Welsh, 2012). This begins very early where attentional systems help direct movement planning (Welsh, Neyedli, & Tremblay, 2013). In one example task showing how RTs evolve with processing time differences for targets that are inhibited (e.g. likes loss targets), Welsh, Neyedli & Tremblay (2013) adapted a cue-target task (Posner & Cohen, 1984) where participants responded to a target that is presented at one of four target locations. Before the target appeared, a non-predictive cue-target would appear for 50 ms. After the cue-target, the actual target appeared at various time-intervals, known as cue-target onset asynchronies (CTOAs: 100, 225, 350, 475 and 600 ms). The results show that at the 100 ms CTOA, RT between cued and uncued targets were virtually equivalent (383 ms) but began deviating as CTOAs increased. The 350, 475, and 600 ms CTOAs showed faster RTs for uncued targets compared to cued targets. The interpretation is that initially the cue draws attention to the location, and then, only after some time is it ignored and ultimately inhibited – similar to our proposal for how the avoidance of loss occurs.

A similar trend is seen in our experiments. For Experiment 1, where non-informative, but high probabilities shapes dominated choice preferences, subjects also showed preferential processing for these shapes in RTs and MTs: subjects reacted faster to high probability single shapes and reacted and moved faster to preferred shapes. Interestingly, in Experiment 2, where no shape was shown to be preferential, RTs and MTs showed no differences. In Experiment 3, which contained the dominantly preferred good-news shapes, subjects reacted faster to good news shapes in single target conditions.

Reaching trajectories are also a metric whereby early perceptual biases can be seen (Chapman et al., 2015; Gallivan & Chapman, 2014). Recording reaching trajectories and calculating deviations from straight hand paths can be indicative of competitive processing between two targets (Chapman et al., 2015). For example, if a subject overwhelmingly prefers a good news vs. bad news target, he/she will reach towards that shape in a straighter fashion. In contrast, if a subject is choosing between two targets with a similar preference (e.g. two targets they want to choose or two targets they want to avoid), they may reach between the choice options before finally moving towards one of the two shapes, allowing for a more curved reach (Gallivan & Chapman, 2014). The most evident bias we find in reach area comes in Experiment 3 where the largest reach area involved the good vs. bad news shape pair, with subjects reaching directly toward good news shapes. The second largest reach was the good vs. neutral news shape pair, followed by the neutral vs. bad news shape pair as seen in figure 3.9A and 3.10. Though it failed to reach significance the same pattern was observed in Experiment 4. Taken together, these results follow the prediction that good news shapes received early preferential processing, and movements to select them were therefore straighter. To summarize, if given very little time (~500 ms or less) to process and decide between options, a preferential bias will appear towards gain instead of loss stimuli. This is reflected in early visuomotor decision metrics such as RT, MT and reaching trajectories.

4.5.2) Later perceptual biases: avoid bad!

If we examine all dependent measures, those that occur after the most elapsed time show the largest indications of loss aversion. This is largely consistent with classical economic decision-making paradigms where subjects are given an ample amount of time to evaluate a hypothetical monetary scenario. A trademark of these classical tasks is that potential losses loom larger than gains. This usually results in the participants avoiding large risk options where they could lose money, making them opt for smaller, but probabilistic gains (Tversky & Kahneman, 1992; Kahneman & Tversky, 1979). Patterns of loss aversion are largely seen in the subjective reports of Experiments 3 and 4, where subjects strongly undervalued bad news shapes compared to others. In the previous section, we specified that gain stimuli received preferential treatment for early perceptual decisions (Summerfield & Tsetsos, 2012), however as we move from early perceptual time windows to later ones, humans seem to become more aware and cautious of potentially harmful or averse stimuli (Chapman et al., 2015; Yechiam & Hochman, 2013; McGraw, Larsen, Kahneman, & Schkade, 2010).

Over the course of time, it appears loss targets accrue more attention, emotion and intensity (McGraw, Larsen, Kahneman, & Schkade, 2010; Delgado, Li, Schiller, & Phelps, 2008; Kahneman & Tversky,1979). By the time subjects have completed a task, their attention is primarily focused on loss aversion compared to going for good. Consistent with this idea when asked to fill subjective reports out at the end of the experiment we see large undervaluing of bad news in Experiments 3 and 4. Moreover, this undervaluing is even more apparent when examining the post questionnaire compared to the pre-questionnaire. Participants vouch that bad news shapes only reward points 25% of the time in Experiment 3 and 38% of the time in Experiment 4 for post-questionnaires. Because subjects had time to reflect on the task that was, these subjective reports were closer to contextual framework of a classic economic decision-making task rather than a perceptual task or a rapid visuomotor decision making task.

I believe the reason for this is because humans can decidedly “think slow”. Kahneman’s’ “system 2” (Kahneman, 2011) affords humans a top-down approach to decision making, allowing for deeper, logical thinking. In doing so, perhaps additional areas of the brain are activated to help consolidate a decision coming from a top-down source. Like bottom-up processes, which produces selection biases for learned "gains" early in the decision-making process, top-down processes may also contain selection biases, resulting in obstacle avoidance (Chapman, Gallivan, Culham, & Goodale, 2011), or loss aversion (Awh, Belopolsky, & Theeuwes, 2012). If given sufficient time to think about a risky decision, losses will undoubtedly loom larger than gains due to the increased neuronal activity of areas that involve attention, emotion and fear (McGraw, Larsen, Kahneman, & Schkade, 2010; Delgado, Li, Schiller, & Phelps, 2008; Kahneman & Tversky,1979).

The major finding in these subjective reports is that loss aversion applies to non-instrumental information in the same way it applies to rewards. Upon receiving pure signals of bad news, subjects conflate that with a pronounced undervaluing of a shape that offers equal reward. The information is inherently tied to the perceived value of the reward, and when asked how often bad new shapes reward points, participants reported an underwhelming percentage in Experiments 3 and 4. This is a point where pigeons differ from humans. Pigeons likely reside exclusively in in early perceptual selection biases, where they promptly select shapes with good information. Likewise, they pay little attention or regard for bad news, which at worst, gives them reduced uncertainty for a non-reward in the future. This suggests there is no "system 2" for pigeons, so the bad news has little to no effect on their decision behavior. In the realm of seeking non-instrumental information about a reward, humans reveal a pronounced dislike for bad news, especially when given sufficient time to evaluate, a trend consistently seen in classic economic decision-making models.

5.0) Conclusion

In conclusion, we originally hypothesized that humans would display similar behavior to pigeons, whereby information was considered most important to reduce uncertainty in a delayed choice task. We decided to pit information against secondary rewards, much like previous pigeon experiments (Mcdevitt, Dunn, Spetch, & Ludvig, 2016; McDevitt, Spetch, & Dunn, 1997; Spetch & Dunn, 1990), but humans showed a greater sensitivity to the probability of rewards than information. When we made all shapes equiprobable in Experiment 2, subjects showed no significant bias towards any shapes, choosing at chance for all shape pairs. In addition, delayed conditions proved to have no effect on choice behavior as participants were more attuned to probabilistic contingencies over delay. Here, we propose at least three reasons for these findings. First, we suggest that the delay effect did not sway behavior because humans have a unique capacity for patience which allows them to recognize the value of a reward even if it is not immediate. Second, regarding information, we propose that humans are extremely sensitive to probability contingencies, even when not explicitly given probabilities. Over the course of hundreds of trials, subjects implicitly learned the probabilities of each shape likely due to reward prediction error pathways in the brain. Finally, we consider the possibility that good news was conflated with bad news, and we hypothesize that receiving potentially bad news led to aversion behaviors in humans. This effectively turned subjects away from selecting informative shapes out of fear of receiving a possible bad news signal.

To test for the effect of valence of information-based decisions, in Experiments 3 and 4 we separated good and bad news into their own shapes. Overall, we saw a clear preference for good news in choice preference, that was corroborated by early perceptual processing measures such as RT, MT and reach trajectories. We also saw a clear avoidance for bad news in choice preferences that was reinforced in our measures of subjective reports. Clearly, humans are more sensitive and risk averse compared to pigeons possibly because of our higher cognitive order. Our ability to think slow affords us the chance to digest, think and therefore dread losses more than gains. In total, we showed that valanced information does have some stark similarities to primary rewards and punishments. Humans behavior in similar fashion to good or bad information the same way they behave towards primary rewards and punishments.

Research on informative signals and other secondary reinforcers play a prominent role in the future of behavioral and cognitive psychology, especially when discussing internet and social media addiction. The various signals, stimuli, and noises seen on numerous social media applications and web pages may be tapping into the mesolimbic pathway of the brain, acting as conditioned reinforcers for social interactions. Hopefully more research is to come on these areas, and we can become more aware as a society on the powerful effects of valanced information on the brain.

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